Information Quality of Credit Ratings and the Role of Credit Rating Agencies: The Impact of Rating Agency Reform in China

A thesis submitted in fulfilment of the requirements for the Doctor of Philosophy

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Declaration

I certify that except where due acknowledgement has been made, the work is that of the author alone; the work has not been submitted previously, in whole or in part, to qualify for any other academic award; the content of the thesis is the result of work that has been carried out since the official commencement date of the approved research program; any editorial work, paid or unpaid, carried out by a third party is acknowledged; and, ethics procedures and guidelines have been followed.

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List of Abbreviations

ABS	asset based securities
AR	abnormal return
bps	basis points
CARs	cumulative abnormal returns
CART	classification and regression tree
CBI	China Bond Index
CBs	corporate bonds
CCCM	China Chengxin Credit Management Co., Ltd.
CCR	China Credit Rating
CCXI	China Chengxin International Credit Rating Company Limited
CCXR	China Chengxin Rating Co., Ltd
CIRC	China Insurance Regulatory Commission
CPs	commercial papers
CRAs	credit rating agencies
CSDC	China Securities Depository and Clearing Corporation Limited
CSRC	China Securities Regulatory Commission
Dagong	Dagong Global Credit Rating Co., Ltd
DBRS	Dominion Bond Rating Service
DID	difference-in-differences
EBITDA	earnings before interest, tax, depreciation and amortisation
EBs	enterprise bonds
EJR	Egan-Jones Rating Company
FSA	Financial Services Authority
FSB	Financial Stability Board
G20	Group of Twenty
GITIC	Guangdong International Trust and Investment Corporation
GRAs	global rating agencies
IPI	investor protection index
IV	instrumental variable
LCIS	Lianhe Credit Information Service Co., Ltd
MBS	mortgage backed securities
MI	Marketization Index
MTNs	medium-term notes

NAFMII	National Association of Financial Market Institutional Investors
NAIC	National Association of Insurance Commissioners
NDRC	National Development and Reform Commission
NRAs	national rating agencies
NRSROs	nationally recognised statistical rating organisation
OECD	Organisation for Economic Co-operation and Development
OLS	ordinary least squares
ORM	ordinal regression model
PBOC	People’s Bank of China
PSM	propensity score matching
SBCR	Shanghai Brilliance Credit Rating & Investors Service Co., Ltd
SCPs	super commercial papers
SEC	US Securities and Exchange Commission
SFE	Shanghai Far East Credit Rating
SOEs	state-owned enterprises
SPC	State Planning Commission
UR	United Ratings
US	United States

Abstract

The rating quality of credit rating agencies (CRAs) attracted substantial attention from researchers after the global financial crisis. In particular, the potential conflicts of interest of CRAs have been widely criticised. Investors expect CRAs to provide accurate and timely ratings as an evaluation benchmark. However, CRAs collect most of their revenue from bond issuers; thus, they have an incentive to cater to issuers, resulting in inflated and non-informative ratings.

This study examines how incumbent issuer-pay CRAs in China changed their ratings strategy in response to a reform in the credit rating industry. This reform introduces a new independent rating agency, China Credit Rating (CCR), which utilised a combination of public utility and investor-pay business models. CCR receives great support from the government which prevent it from the pressure given by issuers and investors. Meanwhile, CCR collects part of its revenue from subscribers, reducing the possibility of government budget shortage. As a result, CCR tends to play a role in disciplining incumbent issuer-pay CRAs' rating behaviour and further improving ratings' information quality. By investigating how incumbent issuer-pay CRAs in China respond to the entry of CCR, this thesis finds that the rating inflation for firms that are also covered by CCR are significantly lower than those not covered by CCR. Moreover, market reaction to rating changes by CRAs on firms covered by CCR is more pronounced after CCR's rating coverage initiation. These results indicate that ratings information quality from CRAs has been improved in the sense that rating inflation is attenuated and ratings are associated with larger market reaction when CCR is present. This result adds empirical evidence to the literature documenting the influence of the introduction of a new rating agency with an alternative business model to issuer-pay rating agencies. This research further shows that the scope of information quality improvement is associated with different information scenarios and the reputation of the rating assigners. Specifically, the information quality improvements are more pronounced for firms facing better investor protection environment (e.g. advanced marketization or better legal rights protection) and for ratings from more reputable CRAs. These results suggest that both internal (i.e. CRAs' reputation) and external forces (i.e. investor protection environment) are crucial to attain higher informativeness for CRAs' ratings with the presence of CCR. In addition, this study provides primary evidence that certification via reputable CRAs is beneficial to issuers in the bond market

in China, with regard to save financing cost. After considering the issuer-reputable CRA match, this thesis finds bonds rated by the most reputable CRAs to be associated with a lower yield spread (higher bond price), revealing the investors' recognition of the rating quality of reputable CRAs. This result is consistent with the traditional certification hypothesis and underlying reputational mechanism. This research further finds such benefits are larger for firms with worse investor protection environment or with higher risks. On the other hand, yield premium is significantly lower in the post-CCR period and for firms not covered by CCR. These results illustrate that reputable CRAs play a role of certifying the quality of firms' debt securities, and this certification effect is reinforced by the entry of CCR.

Overall, this study contributes to a growing body of literature that examines how different business models of CRA affect credit ratings by studying the efficiency of an innovative trial in China, making a supplement to the relevant theoretical models, empirical studies and government proposals. It also complements the study on reputational mechanism of credit rating agencies, calls for investors' attention on the different reactions of different issuer-pay CRAs, and emphasizes the importance of investor protection environment construction. This study also supplements the research on certification role of credit rating agencies, and provides a sight for bond issuers and investors when evaluating bonds rated by CRAs with different reputation.

Keywords: Certification effect, Credit ratings, Informativeness, Investor-pay rating agency, Public rating agency, Rating inflation, Reputation

Chapter 1
Introduction

In this chapter, I will introduce the background of this thesis, including an overview of prevailing business models used in U.S. and the institutions of China's credit rating industry, and a summary of the main findings and contributions of this research. Section 1.1 briefly introduces and compares various business models adopted by credit rating agencies. Section 1.2 briefly introduce the international experience of credit rating industry. Issuer-pay credit ratings agencies (CRAs) and an independent CRA based on a synthesized model is discussed in Section 1.3 and Section 1.4 respectively. Section 1.5 summarizes the main findings and contributions of this study

1.1 Background

Since the subprime mortgage crisis of 2007–2009, criticisms of CRAs, such as Moody's, S&P and Fitch, have regularly made the headlines. In particular, IMF (2009) estimated that the loss on structured financial products was approximately US$4 trillion. A lot of arguments and reform proposals focus on the business models adopted by CRAs. In the following, I briefly introduce the involution of these models.

1.1.1 From Investor-Pay to Issuer-Pay

Initially, to avoid the adverse selection problem between investors and issuers, private CRAs emerged as a solution to the information asymmetry in the 1900s (White 2010) when investors paid CRAs for their rating reports. However, in the early 1970s, this charging model changed to the 'issuer-pay' model under which CRAs charged issuers according to the size and type of the issue. There were two main reasons for this change. The first reason was the widespread use of photocopy machines that led to the problem of 'free-riding', which infringed on CRAs' revenue. In worst cases, CRAs could not make enough revenue to meet their operation expenses (White 2002). The second reason was the surging demand of issuers for credit ratings to assure doubtful investors. A key cause of this was Penn Central's failure to pay back its US$82 million commercial paper (CP) in 1970. This, together with the 1970 recession, caused investors to doubt the solvency of many companies' CPs, which had been booming in the 1960s. When faced by the liquidity crisis caused by investors' refusal to roll over their CPs, issuers wanted to reassure panicked investors by actively seeking credit ratings (White 2002). A regular market pattern was established in which new debt issues had to have at least one credit rating when they came to the market. This increased rating demand allowed CRAs to impose charges on issuers. These two reasons pushed CRAs to change their business model. Moody's and Fitch changed their charging models in 1970, and S&P followed in 1974. Today, a majority of CRAs accept the issuer-pay model and collect most of their income from the companies they rate. Among the current 10 nationally recognised statistical rating organisations (NRSROs), only one, Egan-Jones Rating Company (EJR), still applies the investor-pay model.

Many researchers and policy-makers argue that the current charging model may encourage CRAs to give favourable ratings to issuers. Specifically, CRAs prefer customers who have larger issues (Bolton, Freixas & Shapiro 2012; He, Qian & Strahan 2011) or who are repeat issuers (Bolton, Freixas & Shapiro 2012), resulting in inflated and inaccurate ratings for these issuers. Therefore, the information quality of ratings is reduced. Critics point out that issuer-pay CRAs fear losing clients before their next issue. Thus, the delays in adjusting ratings (weekly information content of ratings) to reflect the changing financial situation of the issuers and the bias towards large companies are widely criticised. Sean Egan of the Egan-Jones investor-pay CRA viewed the issuer-pay model as irredeemable, citing evidence from past failures such as Enron and Parmalat and certain structured products in the subprime crisis (Nielsen 2013).

1.1.2 Comparison of Issuer-Pay and Investor-Pay

Many studies aim to compare different business models of CRAs and the question of who pays the credit rating seems to be a matter of importance. First, ratings are usually more favourable and less accurate/informative under issuer-pay model. For example, theoretically, in Skreta and Veldkamp's (2009) model, issuers are inclined to release the most favourable rating through rating shopping among different issuer-pay CRAs with a naïve investors' assumption. They suggested that this situation can be alleviated by changing to the investor-pay model. Pagano and Volpin's (2010) model advocates that the adoption of the investor-pay model can improve the accuracy of ratings. They further suggest a more modest method that keeps the issuer-pay CRAs but requires issuers to pay an upfront fee that is irrelevant to the rating results to discourage rating shopping. Kashyap and Kovrijnykh (2016) developed a model that analysed optimal compensation schemes for CRAs, and the results differed according to which party paid for the ratings: the social planner, issuers or investors. Larger errors in ratings were found when issuers ordered the ratings compared to investors. From an empirical perspective, Beaver, Shakespeare and Soliman (2006) compared the ratings of Moody's and EJR, and found that EJR's ratings provided more accurate and timely information to investors. Jiang, Harris and Xie (2012) tested S&P's ratings before and after it adopted an issuer-pay model, using Moody's as a benchmark. They found that the ratings of S&P were higher afterwards, which suggests that the issuer-pay model leads to rating inflation. They also undertook cross-sectional analysis to identify whether ratings increased more for bonds with higher potential of generating conflicts of interest, and found that an increase in ratings correlated with inherent conflicts of interest. Cornaggia and Cornaggia (2013) carried out research on Rapid Ratings, another investor-pay CRA, and concluded that this agency provided more reasonable, timely and accurate ratings for investors compared to Moody's, who was more inclined to satisfy the issuers.

Second, different models may attain the same level of social welfare provided that there is high degree of regulatory intervention. For instance, Bongaerts (2013) sets a model with the rational agents' assumption and showed that the investor-pay model, issuer-produced ratings and mandatory co-investments model could all improve social welfare, and that the very high degrees of regulatory intervention were essential in making the above alternative models take hold

Third, many reasons are proposed to explain why the issuer-pay model causes rating inflation and inaccuracy. Rating shopping, through which issuers can take advantage of the issuer-pay business model to increase the ratings for both corporate bonds (CBs) and structured products, is thought to be a significant reason. Issuers may choose the highest rating from the preliminary rating process, and it is assumed that issuers will always pursue higher ratings. This rating shopping may pressure a CRA to increase the rating, causing rating inflation according to the model developed by Skreta and Veldkamp (2009). Fennell and Medvedev (2011) also found evidence of rating shopping from their interviews. Bongaerts's (2014) model found that rating shopping still exists with rational investors. In principle, rating shopping can be exacerbated by competition and competition itself is argued to be responsible for rating inflation and inaccuracy. Bolton, Freixas and Shapiro's (2012) model shows that lower reputation cost, fierce competition and more naive investors provide CRAs with incentives to inflate ratings and that a monopoly should be efficient in solving the rating shopping problem. Bongaerts, Cremers and Goetzmann (2012) identified the tie-breaker role that Fitch plays when Moody's and S&P disagree with each other; this role creates an incentive for issuers to seek a favourable rating from Fitch. Moreover, Becker and Milbourn (2011) suggested that the entry of Fitch coincided with reduced quality of the ratings from incumbent issuer-pay CRAs such as Moody's and S&P; the rating levels increased, the correlation between ratings and market-implied yields fell and the ability of ratings to predict default deteriorated. Their empirical study accepts that competition weakens the reputational mechanism and leads to higher rating inflation; however, it rejects rating shopping as the mechanism.

The above studies mainly advocate that investor-pay CRAs are more reliable than issuer-pay CRAs, with rating shopping and competition put forward as two reasons for this.

1.1.3 Other Proposed Business Models and Debates

1.1.3.1 Other Alternative Models

When comparing issuer-pay models with investor-pay models, the latter receives a high level of support. The investor-produced model, public utility model and platform model have also been proposed by scholars as alternative ways to improve rating quality. For example, Bongaerts (2014) introduced the investor-produced model in which rating agencies are also the end users of the ratings. Diomande, Heintz and Pollin (2009) and Lynch (2010) suggested that the United States (US) launch a public CRA, arguing that the conflict of interest could be managed by modelling the CRA on other successful public independent bodies such as the Federal Reserve or the Supreme Court. Mathis, McAndrews and Rochet (2009) and Richardson and White (2009) proposed the introduction of a platform that would act as an intermediary between issuers and CRAs to prevent issuers from influencing ratings. It would be this platform's responsibility to assign the rating request to a CRA, either randomly or based on the CRA's rating quality.

Many regulatory proposals also support changing the issuer-pay model. For instance, in the US, the *Dodd–Frank Wall Street Reform and Consumer Protection Act* (2010) brought in a wide range of regulatory reforms aimed at reducing the conflicts of interest and increasing rating transparency. The issue of issuer-pay versus investor-pay demands an assessment of the conflicts of interest by the Office of the Controller General. Another proposal relevant to this study is the Franken Amendment, which suggested that the US Securities and Exchange Commission (SEC) should introduce a platform to bring all NRSROs and issuers together through an independent organisation for structured products—the exact platform model that Mathis, McAndrews and Rochet (2009) and Richardson and White (2009) proposed. However, after a two-and-a-half-year study by the SEC, the Franken Amendment was not implemented.[1] In Europe, the Group of Twenty (G20), Financial Services Authority (FSA), Financial Stability Board (FSB) and Organisation for Economic Co-operation and Development (OECD) have all presented proposals for credit rating industry reform. The proposals relevant to this study are those that advocate business model change. For example, the European Commission Consultative Paper (European Commission 2010) advocated a public utility model when it proposed to 'examine the possibility of creating a public European CRA to compete with the private sector', and 'to explore ways to mitigate conflicts of interest in the issuer-pay business model, especially considering a turn back to investor or subscriber pays, a mixture of these two and alternative approaches involving a third party paying or hiring the services'.

1.1.3.2 Debates on Alternative Models

Despite criticism of the issuer-pay model and proposals of alternative models, there are still debates regarding which model should be used. Some people do not believe the issuer-pay model is at fault. For example, big CRAs such as Moody's, S&P and Fitch argue that the conflict of interest is completely manageable (Becker & Opp 2013; Coface 2010; Pagano & Volpin 2010), and CRAs may believe that the long-term revenue balances the rating fee collected from the issuers who ask for high ratings with the reputation cost (House 1995). This means the reputational mechanism of CRAs is elevated to achieve self-regulation.

Moreover, there are some arguments that suggest that other business models also cause rating inflation and inaccuracy due to investors' and regulators' over-reliance on credit ratings. A kind of 'certification' role is allocated to ratings, whereby ratings act as a credit-quality threshold or gatekeeper in financial contracts. Deb et al.'s (2011) study listed the four typical certification roles of CRAs in the use of contracts and market practice, and participants in the market have different expectations of CRAs according to their certification role. Aside from their use in contracts, ratings are also widely used within regulatory frameworks such as supervisory policies (SEC 2002) and in determining net or regulatory capital requirements for banks, securities firms and

[1] See Becker and Opp (2013), SEC (2012) and SEC (2014).

insurance companies (Gonzalez, Sotelino & Savoia 2011). This over-reliance on ratings means that both issuers and investors prefer higher ratings to satisfy the benefit target and regulatory requirements. Therefore, this reliance also dissuades investor-pay CRAs from reducing the rating inflation. The model built by Opp, Opp and Harris (2013) incorporates the regulatory purposes of ratings, and finds that after considering rating-contingent regulation, CRAs provide higher ratings regardless of whether the higher ratings reveal more or less information. This is consistent with Cornaggia and Cornaggia's (2013) findings that Moody's is willing to give relatively higher ratings for bonds at marginal investment grade in order to make them more convenient for regulated investors to buy. Cole and Cooley (2014) suggested that regulatory reliance is a more likely cause of rating inflation and inaccuracy than the business model.

Further, debates also focus on the disadvantages of alternative business models. For the investor-pay model, the free-rider problem is the main challenge (Richardson & White 2009). As mentioned previously, the free-rider problem is one of the reasons why CRAs changed from the investor-pay to issuer-pay model in the 1970s. Although a lower subscription fee can alleviate this problem, investor-pay CRAs will still find it difficult to take advantage of economies of scale and may compromise their rating quality or leave the industry (Fennell & Medvedev 2011). Other challenges of the investor-pay model include pressure from investors to require high ratings (Pagano & Volpin 2010), regulatory use of ratings (Goodhart 2008) and using ratings for structured products (Fennell & Medvedev 2011). Kashyap and Kovrijnykh's (2016) recent model shows that even though the investor-pay model provides more accurate ratings, investors ask for ratings too often, thus dampening their social efficiency.

In regard to the investor-produced model, investors themselves may become the party that benefits most from rating inflation in terms of lower capital charge (Gonzalez, Sotelino & Savoia 2011; Sy 2009). The model developed by Becker and Opp (2013) shows that investor-produced ratings are slightly more inflated when running under the existence of issuer-pay CRAs. This result is in line with Behn, Haselmann and Vig's (2014) suggestion that banks' internal ratings are inaccurate and over-optimistic. Bongaerts's (2014) model also shows that even though investor-produced CRAs can induce more accurate ratings, the traditional issuer-pay CRAs cater better to issuers, thus leaving rare market for investor-produced CRAs.

The public utility model does not eliminate conflicts of interest because the government is also an issuer (European Commission 2010). It is likely that public CRAs would be biased towards sovereign or municipal bonds, or large government-owned companies (Cinquegrana 2009). Other concerns regarding the public utility model include whether rating quality may decline due to insufficient budget funds, how ratings of public CRAs will be perceived by the market and how to maintain high-quality ratings given the absence of competitive market pressure (Fennell & Medvedev 2011).

The platform model has also been questioned. Along with the difficulty in deciding which criteria is used to choose a CRA for a rating request, the platform model also has the potential to decrease incentives for CRAs to provide high-quality ratings as they may be chosen randomly regardless of the quality of their ratings. Additionally, if a platform has a monopoly it would have a role as a systemic regulator alongside its commercial role, thus creating the potential for a new conflict of interest to arise (Fennell & Medvedev 2011). Moreover, Bolton, Freixas and Shapiro (2012) pointed out that the Cuomo plan (issuers pay upfront for ratings) proposed by Pagano and Volpin (2010) alleviates the conflict of interest but cannot solve rating shopping. Bongaerts (2014) suggested that the main reason for rating inflation is the private benefit for issuers and investors. His model suggested that the investor-pay model, investor-produced ratings and Franken Amendment may all have very limited potential in improving social welfare—the issuer-pay CRAs would need to be banned to make any of them effective.

As discussed, the proposed alternative models all have their own drawbacks and cannot perfectly eliminate the conflict of interest between CRAs, investors, issuers and government, thus providing no conclusive solution. In practice, the launch of CRAs with alternative models has been very limited. For example, the French credit insurer Coface wanted to sell its investor-produced ratings to other investors, but this never eventuated (Coface 2010). Another example is Markus Krall, a senior managing partner at Roland Berger, who tried to set up a European not-for-profit investor-pay CRA. This plan was finally abandoned due to a lack of interest from investors (Nielsen 2013; Spiegel 2012). Moreover, the SEC did not pass the Franken Amendment, thus keeping the present issuer-pay CRAs prevalent in the market. Black Rock and PIMCO are two examples of companies who offer investor-produced ratings. However, while their ratings are adopted by the National Association of Insurance Commissioners in the US to determine capital requirements, the companies only focus on commercial mortgage-backed securities in the case of Black Rock and residential mortgage-backed securities in the case of PIMCO; thus, investor-produced ratings are not widely applied in the industry.

Apart from the drawbacks of the alternative business models, the nature of the credit rating industry, large economies of scale, extensive time required to establish reputations, network externalities and high fixed costs also create significant barriers to entry into the market (Fennell & Medvedev 2011) and are further reasons why there are so few examples of the alternative models in practice. This lack of widespread practical cases of introducing other business models into the credit rating industry creates a barrier to empirical analysis of the effectiveness of these alternative ratings models.

For the aforementioned reasons, issuer-pay CRAs have historically dominated the ratings industry around the world and, even after many regulatory proposals, no individual country or area—except China—has widely applied other alternative models. China launched an independent CRA (CCR) in 2010 that combined the public utility and investor-pay models. This unique undertaking provides us with an experiment through which to analyse whether this specific CRA with its new business model affected the rating information quality of the incumbent issuer-pay CRAs in China.

1.1.4 Certification Effect of Reputable CRAs

After the subprime crisis and sovereign debt crisis in Europe, the failure of CRAs has been widely discussed by the public and academia. The discussion was directed at their capital: their reputation. There are several branches of studies on the reputation of CRAs and financial intermediaries in general. Nevertheless, this thesis will focus on the relationship between intermediary reputation and security price.

Theoretically, there are still inconsistencies between the certification hypothesis and market power hypothesis in relation to the role of a financial intermediary's reputation. In terms of the certification effect via reputation of the CRAs, some commentators believe that the reputational mechanism can alleviate any conflict of interest to some extent. When issuer-pay CRAs consider the long-term reputation cost, they tend to provide more informative ratings to avoid investors' or regulators' derecognition of their rating inflation (Bar-Isaac & Shapiro 2013; Bolton, Freixas & Shapiro 2012). Further, Goel and Thakor (2010) found that CRAs' concern over their reputation can induce them to invest more, and that reputation tends to dominate any conflicts of interest in the industry (Covitz & Harrison 2003). Fischer's (2015) model uses a dynamic setting to capture the effects of CRAs' reputations, and the author found that low-quality bond issuers generally tend to match low-quality CRAs. However, the same debate between certification and market power also exists in the credit rating industry. For example, model built by Mathis, McAndrews and Rochet (2009) suggested that agencies increase their ratings using their cumulative reputation. The truth-telling incentives are weaker when CRAs have more business from rating complex products. Empirically, there has been limited research on the influence of the reputation of China's CRAs on bond-issuing prices. For a long time, the reputation of issuer-pay CRAs in China was criticised (Kennedy 2008; Lee 2006).

Generally speaking, the empirical studies on the relationship between bond yield and CRA's certification role are still sparse and inconclusive, while the inconclusive evidence mainly stems from the differences in the sample and time period selection. China provides a unique setting in which many issuer-pay CRAs are competing; thus, I have sufficient criteria to split them into reputable and non-reputable groups. The entry of CCR gives us an exogenous shock to further test the certification hypothesis. This thesis complements the literature that supports the certification effect of reputable CRAs in the bond market.

1.2 International experience from the US

The United States has the largest bond market in the world, whose outstanding amount is about USD 35.78 trillion at the end of 2014. And three credit rating agencies, Moody's, Standard & Poor's (S&P) and Fitch nowadays dominate the international credit rating industry. They hold 97%-98% of U.S. bond market[2], and hold a collective global market share roughly 95%, with Moody's and S&P having around 40%, and Fitch 15% (Caouette et al. 2008). Therefore, the U.S. bond market is a typical example of the mature markets internationally, and then the institutional background of international credit rating industry is mainly about the U.S. situation.

1.2.1 The history of CRAs

The emerging of credit rating industry started from 1909, when John Moody publicly rated the American railroad bonds (White 2010), and it extended its business to utility

[2] Status quo for rating agencies (chart of percentage of outstanding credit ratings reported to the SEC 2007 and 2011; and Moody's revenue and income 1996, 2000, 2010, 2012)| mcclatchydc.com

and industrial bonds in 1910[3]. Poor's Publishing Co. and Standard Statistics[4] followed in 1916 and 1922 respectively. Then in 1924, the Fitch Publishing CO.[5] began its business. Internationally, the transmission of capital flow from banking system to financial market leaded the need for CRAs not only in the developed but also the developing countries (Dale & Thomas 1991). Together with U.S. four largest CRAs, one other U.S., one British, two Canadian and three Japanese firms are listed among the world's "most influential" rating agencies by the Financial Times in its publication Credit Ratings (Cantor & Packer 1995). As the development of the international financial markets, credit rating agencies expanded their business overseas.

All the ratings given by CRAs are to indicate the possibility of securities default. The symbols are created by CRAs themselves to rank the risk of default, and generally the higher the ranking the lower the risk. Gradually, CRAs wanted to add accuracy to the ratings[6], so they introduced plus and minus symbols. Other modifications including the "watchlist" have also become standard.

The development of CRAs from one part comes from the booming of capital market, from another part it is because of the regulation. The power of influence of CRAs is given and enforced by the regulation to some extent. In U.S., bank regulators started to require that banks needed to heed ratings when they invested in bonds from 1930s, and banks were prohibited from buying speculative bonds in 1936 (Richardson & White 2009). This rule is still in place today, enacting by Office of the Comptroller of the Currency (OCC). In the next few decades, insurance regulators related the minimum capital requirement for insurance companies to the bond ratings held in their investment portfolios. The same method began to be used by the federal pension in 1970s.

Then an important organization was founded in 1975 by the Securities and Exchange Commission (SEC). Similar to the requirements of other financial regulators, SEC wanted broker-dealers to keep sufficient capital levels, and it should be related to the bonds' ratings in their investment. However, SEC found that the qualities of CRAs were uneven, and there was no clear statement on which CRA the financial institutions

[3] Moody's company was acquired by Dun & Bradstreet in 1962; Moody's was spun off as a freestanding company in 2000.
[4] The two companies merged, to become Standard & Poor's, in 1941; in 1966 that company was absorbed into McGraw-Hill, where it remains today.
[5] Fitch merged with a British rating firm, IBCA, in 1997 and is now a subsidiary of FIMILAC, a French business services conglomerate.
[6] Fitch in 1973, S&P in 1974 and Moody's in 1982.

should heed, leaving the possibility that ratings of bogus CRAs could be used for regulatory purpose. SEC believed this would cause the bad CRA drive good ones, leading potential risks from regulatory perspective. Thus SEC established nationally recognized statistical rating organization (NRSRO), a fully new regulatory category. Moody’s, S&P and Fitch were immediately recognized by NRSRO, and then other financial regulators quickly accepted this category and applied it to their requirements.

The influence of CRAs was reinforced by regulation again. And the monopoly situation of credit rating industry was also intensified because of the barrier created by SEC and the widespread recognition of NRSRO designation by bond market investors.

In the next 25 years, there were four more CRAs entered the NRSRO, but the total number at the end of 2000 came back to the original three as Fitch merged the new entrants. The bankruptcy of Enron in November 2011 drove the attention of media, scholars and congress to the failure of the three NRSORs, because they still kept investment grade on Enron’s debt five days before its collapse. After the congressional hearings and Sarbanes-Oxley Act of 2002, SEC did some simple reports on credit rating industry, yielding a more widespread recognition of the NRSOR process while not mentioning the barriers to enter the category. After that wave, SEC designated the fourth and fifth NRSRO in 2003 and 2005[7], but the process was still sluggish. To prompt SEC and clear the designation opacity, Congress passed the Credit Rating Agency Reform Act (CRARA). The Act was signed into law in September 2006, specifying criteria for designating NRSROs and requiring the transparency of NRSRO process. After the passage of the Act, SEC has added six NRSROs, but in 2011 one Japanese CRA withdrew its NRSRO registration, thus the total number of NRSROs till now is 10.

In total, the need of credit rating started from the development of financial market, and from 1930s, the power of CRAs has been gradually enforced by the financial regulators. The regulators play a very important role on setting the barrier of market entry, creating a monopoly market and ensuring the dominance of Moody’s, S&P and Fitch.

[7] Dominion Bond Rating Services, a Canadian firm was designated in 2003. A.M. Best, a specialist on insurance companies’ obligations was designated in 2005.

1.2.2 The charging models of CRAs

Credit rating agencies originally charged fee from the investors by selling their reports or publications. But from the early 1970s, this charging model began to change to the "issuer-pay", which means the CRAs charged the issuers according to the size and type of the issue. There are two main reasons for this change. Firstly, the widespread use of photocopy machines leaded to the problem of "free rider", which decreased the CRAs' revenue. The CRAs even did not have enough money to support their operation (White 2002). The second reason is the urgent demand of issuers for credit ratings from 1970. In 1970, Penn Central failed to pay back its $82 million commercial paper. And together with the 1970 recession, investors started to doubt the solvency of a lot of companies' CPs, which was booming from the 1960s. Faced with the liquidity crisis caused by investors' refusal to roll over their CPs, issuers wanted to reassure those panic investors by actively seeking credit ratings. And then a regular market pattern was established that new debt issues must had at least one credit rating when they came to the market. This increasing rating demand let CRAs found they can impose charges on issuers. Moody's and Fitch changed their charging models in 1970, and S&P followed in 1974.

A majority of CRAs accept issuer-pay model and collect most of their incomes from the companies they rate. Among the current 10 NRSROs, there is only one exception, Egan-Jones Rating Company (EJR), still applies the investor-pay model.

The fees charged by CRAs are related to the issues size and category, and CRAs have the right to change the charging standard. According to Cantor and Packer (1995), a typical fee on a long-term corporate bond issue ranges from 2 to 3 basis points of the principle for each year when the rating maintains. And normally, the fee for each issue has both a minimum and a maximum, which can be negotiated for frequent borrowers. The charging fees have a tendency to increase in recent years. For instance, the U.S. ratings fees of S&P for corporate bonds have been increased to up to 6.15 basis points with minimum fee $92,250; the fee for structured issues is also raised to up to 12 basis points (Standard & Poor's Rating Services U.S. Ratings Fees Disclosure 2015). Moody's and Fitch are charging more as well. It seems that the 2008-09 financial crisis did not change the dominant position and pricing power of the three big CRAs, and they also argue the competition of this industry is focused on rating quality rather than price (Faux 2011).

This change of the charging model causes the discussion about the rise of conflict of interest (White 2002). Many researchers believe the current charging model may encourage CRAs to give favourable ratings to issuers, which will lead to the rating inflation and descending rating accuracy (Skreta & Veldkamp 2009). Especially for the structured financial products such as CDS, because CRAs directly engaged in the designing process, this conflict of interest is even worse (Richardson & White 2009). The conflict also comes from CRAs' fear to lose the clients for their next issues. Then the delays in adjusting ratings to reflect the changing financial situation of the issuers and the bias to the large companies are criticized (Bolton, Freixas & Shapiro 2012). Faced with these accuses, CRAs themselves argue they keep the rating quality by reputation mechanism and they focus on the economic cycle thus do not change the ratings frequently.

1.2.3 The process of getting rated

Although there are differences in the details of rating process for various CRAs, they all generally follow the basic routine. The new issuer will request a preliminary meeting with credit analysts. Sometimes, raters will lease a preliminary rating based on public information without a meeting. Then it is the time for issuers to decide whether or not to proceed the borrowing and rating. When the issuer proceeds, the rating agencies will assign a team of analysts to analyse the firm. Generally, firms will provide the raters with five years' financial statements, future financial plans and operation forecasts. The analysts will also meet with the senior officers of the issuers, including the CEO, CFO typically, and they will discuss the operation of the company in depth. After this investigation, the team will attend a rating committee, presenting their qualitative and quantitative analysis and their recommended rating. This rating committee is always composed by the team leader, other analysts familiar with the industry and some senior officers of the agency. And the final rating result is decided by the voting result of this committee. After publication of the rating, CRAs will keep on monitor the ratings on an ongoing basis. Jewell and Livingston (1999) also briefly introduce the rating process of agencies.

All of the above are for solicited ratings, which means CRAs can get paid through this process. But for unsolicited ratings which are not requested by the issuers, CRAs have various policies. Moody's and S&P rate all SEC-registers, US corporate securities, no matter they are paid or not (Langohr & Langohr 2008). Fitch began unsolicited rating in

2001, targeting high-profile issues with discrepancy. The unsolicited ratings of S&P are based on public information while Moody's and Fitch include a certain amount of inside information (Behr & Güttler 2008). Ratings without request are always lower than soliciting ratings, and are criticized for its insufficient information. Recently, some rating agencies started to withdraw its unsolicited ratings. This is very different from the situation of China, which we will discuss later.

During the rating process, new issues always receive more than two ratings from different CRAs. The dual ratings are very common in international bond market. In developed countries, the long-time development of financial market leads to the feature of dual rating. At the meantime, the regulations put the dual rating in action as well, especially for the emerging market. Most dual rating system is applied to particular categories of securities, such as the structured financial instruments. Dual rating system causes the split ratings, when CRAs have different opinions on one same issue. From 1983 to September 2008, 14,005 U.S. new issuing corporate bonds have dual ratings from Moody's and S&P, and 6,867 (49.03%) issues among them have split ratings (Livingston & Zhou 2009). This is also not the situation of China's market.

1.3 Issuer-Pay CRAs in China

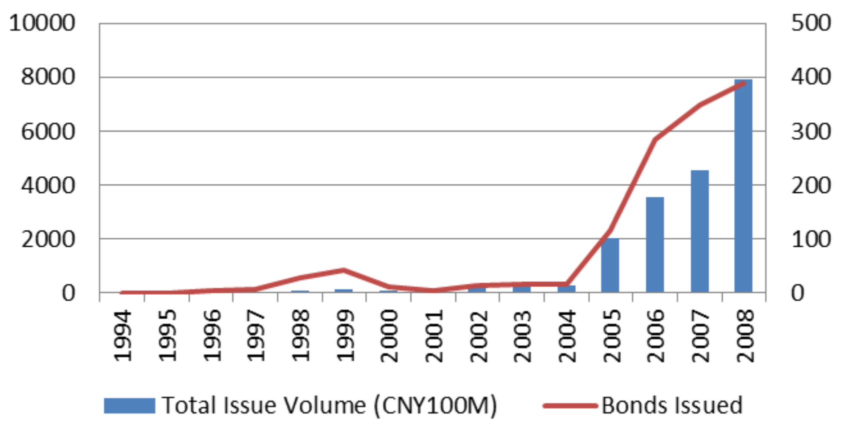
1.3.1 The History of China's Credit Rating Agencies

China's CRAs developed in conjunction with the growth of China's financial market, particularly the bond market. In the mid-1980s, China launched a CB market and CRAs emerged to rate stocks, insurance companies, banks and bonds in the domestic market. During that decade, China's CB market experienced a boom and, in 1987, the People's Bank of China (PBOC) issued 'temporary regulations on the management of corporate bonds'. The PBOC also encouraged its branches to create credit rating departments in their own provinces and, from 1989, some of these departments became independent CRAs. The number of CRAs surged to over 90 during this period. However, during this time, the PBOC set the coupon rate according to the prevailing one-year bank deposit rate (an additional 40%). This meant that ratings had no influence on the bond-issuing yield. Further, ratings were not disclosed to the public and were used by government authorities to approve issue applications (Chen 2003).

This boom era led to a disastrous bond default in the mid-1990s, with massive borrowers refusing to pay the interest or principal. In the Liaoning and Jilin provinces, more than half of the bonds went to default. Thus, the local government and PBOC had to pay out, with the total cost estimated to be between RMB 3 and 8 billion (Kennedy 2008). The collapse of Guangdong International Trust and Investment Corporation and the Asian financial crisis compounded the situation. In 1999, the Chinese government moved the right of CB approval to the State Planning Commission (SPC; renamed the National Development and Reform Commission [NDRC] in 2003). Shortly thereafter, the SPC applied a quota system and only large state-owned enterprises with 100% bank guarantee could issue CBs. The coupon rate was set at around 150–250 basis points (bps) above the one-year bank deposit rate (Fleisher 2008). At the same time, in December 1997, the PBOC designated nine of the existing 50 CRAs as agencies who could rate the publicly issued CBs. They were China Chengxin Rating Co., Ltd (CCXR); Dagong Global Credit Rating Co., Ltd (Dagong); Shenzhen Credit Rating (the predecessor of Pengyuan); Yunnan Credit Rating; Changcheng Credit Rating; Shanghai Far East Credit Rating (SFE); Shanghai Brilliance Credit Rating & Investors Service Co., Ltd (SBCR); Liaoning Credit Rating; and Fujian Credit Rating Committee (the predecessor of Lianhe). Subsequently, China's bond market and credit rating industry experienced low development in the following years. In 2003, NDRC claimed that all CBs had to be rated by CRAs who had rating experience from 2000 onwards, and the number of qualified CRAs decreased from nine to five (CCXR, Dagong, SFE, SBRC and Lianhe). During this period, CRAs played a very small role in the bond-issuing process, as the approval of CBs was decided by the NDRC and the price of bonds was set by the Interest Rate Section of the PBOC's Monetary Policy Division. Moreover, all CBs were guaranteed by a state-owned bank or enterprise.

In the following years, several of China's bond market milestones were reached. First, in 2005, the PBOC created the short-term CP. The maturity of a CP is one year or less, and all firms can apply to issue it without the requirement of guarantee (the price is decided by the market). The PBOC also authorised the aforementioned five CRAs to give credit ratings to the CPs. Second, in 2008, the PBOC created a new type of bond—the medium-term note (MTN)—with the same features as a CP, but a longer maturity. Both the CP and MTN are traded on the interbank market regulated by the PBOC. The volume of CPs and MTNs saw a rapid increase (see Figure 1.1) and the business of CRAs surged. More importantly, credit ratings began to have some influence on both the issuing coupon rate and the bond price on the secondary market (Tu 2006). This proved that the effectiveness of China's CRAs was strongly related to the level of maturity of the domestic financial market. This is also why I chose data from 2006. The third breakthrough came in 2007, when the authorising power for CBs was split between the NDRC and the China Securities Regulatory Commission (CSRC). From this point onwards, the CSRC was mainly in charge of the bonds issued by listed companies on the Shanghai and Shenzhen exchange markets, known as enterprise bonds (EBs). Meanwhile, the NDRC started to focus on bonds issued with the main purpose of infrastructure construction. Subsequently, EBs were issued and traded on the exchange market while CBs were issued and traded on both the exchange and interbank markets. After this separation, the CSRC issued provisional administrative measures on the credit rating business in the Chinese securities market to regulate the CRAs for EBs. This authorisation split added one more supervisor to the credit rating industry.

Figure 1.1: Volume and Number of Issues on China's Bond Market

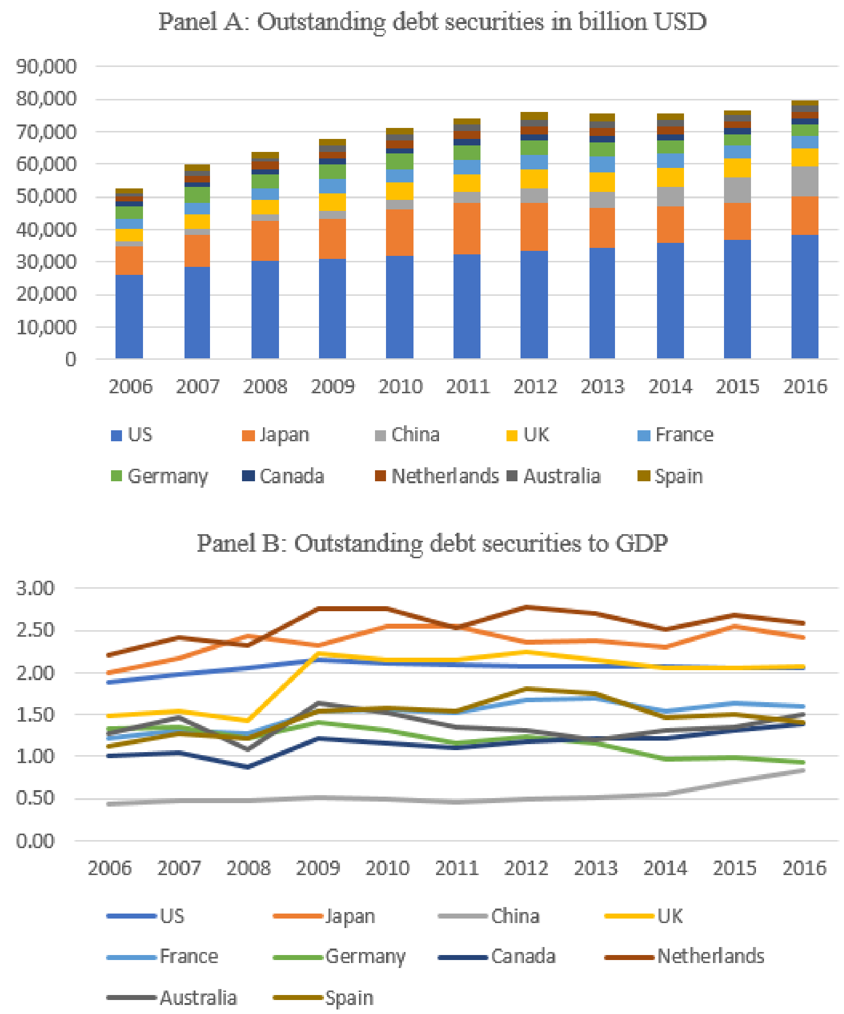


Note: Bonds including non-financial institutions' CPs, MTNs, CBs and EBs.
Source: China Bond, Wind.

Till now, China has the third largest outstanding bond volume around the world, just following the US and Japan (Figure 1.2). And China's government is gradually opening its bond market to foreign investors[8], which makes this study more significant to help investors to better understand China's bond market.

Figure 1.2 China's debt securities in the world bond market

[8] http://www.fdi.gov.cn/1800000121_23_72846_0_7.html 中国人民银行公告〔2016〕第 3 号; http://www.pbc.gov.cn/goutongjiaoliu/113456/113469/3330621/index.html 内地与香港债券市场互联互通合作管理暂行办法》



Generally speaking, the role of China's CRAs is appointed by financial regulators, similar to in the US. The first regulation of CRAs was the revised version of CB regulation issued by the PBOC in 1992. It stated that issuers '*could*' seek ratings from CRAs during their application process. Subsequently, in 1997, the PBOC changed this regulation to 'issuance of corporate bond *must* have ratings', which reinforced the position of the nine recognised CRAs. In 2003, the China Insurance Regulatory Commission (CIRC) approved insurance companies to invest in CBs and only recognised the ratings from China Chengxin International Credit Rating Company Limited (CCXI),[9] Dagong, Lianhe and SFE. In the same year, the NDRC also gave five CRAs—CCXI, Dagong, Lianhe, SFE and SBCR—the qualification to rate CBs. Further, from October 2003 onward, the CSRC required listed companies to hire CRAs when they launched bonds. Over the next few years, this requirement was applied to different categories of bonds, such as the subordinated debt of banks and insurance companies,

[9] A joint venture of China Credit Rating Co., Ltd (CCR) and Moody's.

Asset Based Securities (ABS), CPs and MTNs. Today, all publicly issued bonds are required to be rated by qualified CRAs.

1.3.2 The Existing Credit Rating Agencies in China

Currently, there are a total of nine issuer-pay CRAs in China who can issue ratings on the bond market. The 'big four' CRAs in China are CCXI, Lianhe, Dagong and SBCR. From 2006 to 2015, more than 90% of the market's non-financial institutions' CPs and MTNs were shared by the big four. For CBs, about 70% of issuers were clients of the big four.

CCXI was the first joint venture credit rating company in China. It was founded in August 1999 by China Chengxin Securities Credit Rating Company Limited (now China Chengxin Credit Management Co., Ltd [CCCM]) and Fitch (1998). CCCM is a private CRA that was one of the first CRAs in China (established in 1992). CCXI then had permission to rate CBs. In July 2004, Fitch announced its divestment from CCXI due to a desire to focus on the domestic market (Fitch 2004). In 2005, further reform of China's bond market attracted another investor: Moody's. In September 2006, Moody's bought up to the regulatory cap of a 49% share of CCXI and started to provide management and technical support on rating methodologies and training of analysts (PeopleDaily 2006). Since CCXI acquired the rating qualification early and has expertise adopted from two internationally famous CRAs, it has a generally higher market share in China's bond market (see Appendix 2.1) and a better reputation. At the end of 2015, CCXI had more than 200 employees and rated issuers throughout China. Until the end of 2015, CCXI had qualifications and licences from PBOC in 1997, NDRC in 2003 and CIRC in 2003 and 2013[10].

In 1995, the Fujian Credit Rating Committee was formed and, in July 2000, Lianhe was established after reorganization and a name change. From its inception, Lianhe had the permission to rate CBs. In August 2007, Fitch returned to China's market and bought a 49% share of Lianhe from its original shareholder, Lianhe Credit Information Service Co., Ltd (LCIS). Lianhe thus became the second joint venture CRA in China. At the end of 2015, Lianhe had about 200 staff and its business was conducted throughout China. It had the same qualifications as CCXI. Since CCXI and Lianhe are both joint venture firms, they do not have approval from the CSRC to rate bonds on the Shanghai and

[10] CIRC 2013: The recognition of seven credit rating agencies.
http://www.circ.gov.cn/web/site0/tab5214/info3887803.htm

Shenzhen exchange markets.[11] However, their brother companies (with the same domestic shareholders) have this qualification.

Dagong, founded in March 1994, is one of the earliest CRAs in China. In 2010, the SEC rejected Dagong's application to enter the NRSRO because the SEC did not consider it to have the capability to analyse a transnational corporation. Dagong does not have the issue of foreign capital. It has full licences[12] to rate all categories of bonds on different markets and was also recognised by the CIRC from 2003. Dagong can rate borrowers throughout China and employed more than 300 workers at the end of 2015.

The other issuer-pay CRAs in China—SBRC; CCXR; United Ratings (UR); Pengyuan Credit Rating Co., Ltd (Pengyuan); Golden Credit Rating International Co., Ltd (Golden) and SFE—are all national rating agencies.

1.3.3 The Charging Models of Credit Rating Agencies

China's credit rating industry did not experience the change from an investor-pay to issuer-pay model. Initially, China's CRAs collected most of their revenue from borrowers. One agency, Xinhua Far East, successfully sold their reports on the qualities of approximately 100 listed companies on China's stock market. This business model started from early 2002, but it was not applied to the whole bond market. It disappeared with the fall of SFE. Till the end of 2015, the only investor-pay rating agency in China is CCR, and only subscribers can read their reports in detail. Investors without a subscription can only review the ratings and brief introduction of specific firms. This situation is very similar to that of the US; however, China's CRAs did not accumulate a reputation from the investor-pay model compared to the international big three who had around 60 years of investor-pay history.

A fierce price fight among CRAs over the charging fee led to malignant competition (Chen 2010). From October 2007, urged by the PBOC, China's five major interbank CRAs (CCXI, Lianhe, Dagong, SBRC and SFE) started to implement the Rating Charge Self-Discipline for CRAs on the Interbank Bond Market. Under this agreement, these five CRAs agreed to abide by the guiding opinions of the PBOC in relation to the management of credit rating and the People's Republic of China's financial industry

[11] CSRC 2007 Decree No. 50: Provisional Administrative Measures on the Credit Rating Business in Chinese Securities Market.

[12] Dagong receive the recognition from PBOC in 1997, NDRC in 2003, CIRC in 2003 and 2013, CSRC in 2007.

standard specification for credit rating in the credit and interbank bond markets. This established a common minimum charging rate in order to prevent a conflict of interest when rating bonds. For non-financial institutions' CPs, the minimum price for rating the issuers and bonds was 100,000 RMB and 150,000 RMB respectively. For long-term bonds, the minimum charging rate for CBs, convertible bonds and MTNs was 250,000 RMB, while the price for financial institutions' bonds was more than 350,000 RMB. The fee of the follow-up rating for long-term bonds was charged by the number of years at 20% of the initial rating fee. Moreover, the minimum charging rate was 600,000 RMB for ABS and 1,000,000 RMB for mortgage backed securities (MBS). This self-discipline agreement was also applied to other CRAs and treated as a normal standard for the bonds on the exchange market. Further, in 2008, the PBOC released the Notice of the People's Bank of China on Strengthening the Management of the Credit Rating Practices in Interbank Bond Market that required CRAs to report their potential clients and business to the PBOC before starting the rating process. The minimum time for finishing the rating report required by this regulation is 45 days. This also prohibits price competition and assures the report quality to some extent.

Therefore, contrary to the US, the minimum charging rate of China's credit rating industry is decided by the government. In practice, due to their fear of losing clients, CRAs in China generally charge the minimum rate. From this perspective, it is obvious that the international big three CRAs have more power in the market as they can increase the rating price. In other words, China's credit rating industry has more intense competition.

1.3.4 The Process of Getting Rated

The process of China's bond rating is similar to that of the US. There is also a preliminary rating process. During this period, companies who want to issue bonds will be led by underwriters in seeking appropriate CRAs. Generally, CRAs will give an initial rating based on public information and materials supplied by borrowers and underwriters. Issuers will compare the ratings under the consultation of underwriters. During this process, they consider both the ratings and reputation of different CRAs, or stipulate the value of the ratings and how much the ratings can save them in costs. After deciding on the agency, the issuer and CRA sign a contract and report this to the CRA's supervisors. Subsequently, a team made up of at least two rating analysts will go to the issuer's office to commence an investigation. The rating processes and documents need to follow the relevant standards issued by the PBOC and the CSRC. After a vote by the rating committee, the final credit rating result is released to the public. If the issuers disagree with the final rating, the CRA will not release the result. The CRA then monitors any issues on an ongoing basis.

Unlike the US, unsolicited rating is not prevalent in China. Another key difference is in the area of double rating. Most of China's bonds are rated by only one agency. Except for asset-based securities [13] and super commercial papers (SCPs), [14] there are no requirements for double rating. Further, China's issuers are rarely willing to seek more than one CRA to rate their bonds.

1.4 China Credit Rating's Institutional Background

As mentioned in Section 1.1, the new CRA that combines the public utility and investor-pay models is CCR. It was founded in August 2010 by the National Association of Financial Market Institutional Investors (NAFMII) with 50 million RMB in registered capital. NAFMII is a self-regulated organisation whose purpose is to propel the development of China's over-the-counter financial market under the direction of the PBOC. The registered capital comes from the membership fee collected by NAFMII. Although CCR announced its total independence from the PBOC,[15] the PBOC is in charge of its shareholder NAFMII[16] and both CCR's chairmen of the board and its chairman of the supervisory board have working experience at the PBOC.[17] Thus, due to its support from the government, CCR has the feature of a public utility model. However, CCR implements the investor-pay model. CCR releases its ratings through ChinaBond, Wind and its own website. All investors in the market can see its rating announcements and rating notches. However, only subscribers receive full access to CCR's current and historical rating reports and customised services from CCR, such as reports for specific companies or industries.[18] CCR commenced business in 2012. From 2012 to 2015, CCR covered 870 companies who had already issued bonds on the market. Additionally, CCR regularly releases relevant industrial credit analysis reports

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[13] PBOC, CBRC, CSRC 2012: Notice on further expansion of the securitisation of credit assets. (关于进一步扩大信贷资产证券化试点有关事项的通知).

[14] SCPs must have double ratings; one of from an investor-pay agency. Issuers who launch SCPs must have both ratings above AA+. http://news.cnstock.com/news/sns_jr/201310/2780021.htm

[15] http://www.nafmii.org.cn/ztbd/zzzxpgyxzr/201202/t20120227_4048.html

[16] http://www.nafmii.org.cn/fzlm/GYWM/201202/t20120227_4278.html

[17] http://www.chinaratings.com.cn/AboutUs/Governance/

[18] CCR provides a range of service packages to investors with different levels of subscription fees.

and credit risk perdition models to its customers, as well as organising credit risk–related training.

Being a combination of the investor-pay and public models, CCR has some unique features. First, it has a connection with the government (the PBOC) and declares its purpose as not-for-benefit. Therefore, to some extent, it has immunity from pressure from both investors and issuers who require higher ratings as mentioned in Section 1.1. Second, CCR applies a sufficient approach to prevent the excessive free-riding problem, which is the main issue for investor-pay CRAs. The investors (e.g., banks, securities firms and insurance companies) subscribe directly to CCR for each rated asset class in which they conduct business. CCR allocates a unique subscriber number to each investor per asset class. Each time a subscriber wants to download the full-version rating report or rating database, they enter the relevant user number and validated subscriber number. The advantages of this approach are described in Deb et al.'s (2011) study. Third, as a combined model, the subscription fee solves the problem of lacking incentives to provide high-quality ratings and the shortage of government funds that are the main concerns of the public utility model. Last, CCR's ratings are not considered in the bond valuation system of ChinaBond; thus, CCR does not have a powerful influence on the bonds' price. In addition, ratings from CCR are not widely included in the regulatory framework. Therefore, for the investors' benefit and from the perspective of regulatory purpose, CCR has less pressure to inflate ratings than incumbent issuer-pay CRAs. CCR thus combines the advantages of the investor-pay and public utility models, while at the same time limiting and controlling their drawbacks.

Panel A of Table 1.1 shows the comparison of ratings by CCR and issuer-pay CRAs after 2012. It compares every firm–year–CRA rating given by issuer-pay CRAs with the corresponding rating given by CCR. The ratings by CCR are similar to the benchmarks for all issuer-pay CRAs and no one rating given by CCR is higher than that of the issuer-pay CRAs. Panel B of Table 1.1 presents summary statistics for issuer-pay CRAs' and CCR's ratings between 2012 and 2015 and the t-test results of mean differences between groups. CCR's ratings are significantly lower than those by issuer-pay CRAs at a 1% level of significance.

According to CCR's internal policy, it selects some issuers to rate randomly or at the request of its subscribers. The entry of CCR does not squeeze the market share of the existing issuer-pay CRAs because CCR cannot rate CPs, MTNs, CBs or EBs. However, the opinions and trust of bond investors are likely to be affected by the relatively lower ratings given by CCR that may reveal the low quality of ratings by incumbent CRAs. By reviewing significant rating differences, supervisors are also expected to apply stricter scrutiny or punishment on issuer-pay CRAs. The basic hypothesis of this study is that incumbent issuer-pay CRAs, based on these two concerns, were forced to adjust their rating behaviour to provide more conservative, timely and accurate ratings following the entry of CCR, resulting in a general improvement in rating quality.

Table 1.1: Statistics of Comparison between Ratings Given by CCR and Issuer-Pay Credit Rating Agencies

Table 1.1 presents a comparison between ratings of issuer-pay CRAs and CCR between 2012 and 2015. The sampled firms have been rated both before and after 2012. Panel A compares every firm–year–CRA rating given by issuer-pay CRAs with the rating given to that firm in the same year by CCR. Panel B presents the mean differences of ratings given by CCR and issuer-pay CRAs between 2012 and 2015. *Rating* is a numerical value based on a notch basis from 1 to 5. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels respectively.

Panel A: Comparison of ratings between CCR and issuer-pay CRAs

Issuer-pay ratings	>CCR	=CCR	<CCR
N	3066	1106	0
Proportion	73.49%	26.51%	Nil

Panel B: Mean difference between ratings of CCR and issuer-pay CRAs

	Issuer-pay CRAs	CCR	(Issuer-pay—CCR)
Mean rating	4.070	3.042	1.028***
N	11,419	1972	

1.5 Findings and Contributions of This Study

This study discusses three problems with regard to CRAs in Chapter 2, 3 and 4, and they are closely related to each other. Chapter 2 examines whether the incumbent CRAs in the treatment group have significantly reduced their ratings in comparison to the control group, as a response to the coverage by CCR, using a DID identification approach which helps control for confounding effect (i.e. other macro-economic shocks). The analysis documents that the incumbent CRAs have significantly reduced their ratings in the treatment group compared to the control group, subsequent to the entry of CCR.

To further understand the results, I test how this discipline effect has changed the information content of rating change announcements made by incumbent CRAs in Chapter 2. Using an event study approach, I find that CCR's coverage has triggered a larger market reaction to incumbents' rating downgrade announcements. In Chapter 2 and 3, I also find the reputation concerns of the incumbent CRAs is one of the mechanisms through which the CCR's coverage reduces information asymmetry and enhances the rating quality of the incumbent CRAs. I find that only reputable CRAs react and lower their ratings as a response to CCR's coverage, compared with non-reputable CRAs. Moreover, the effect of CCR's coverage on the information content of incumbents' downgrade announcements is significantly larger for reputable CRAs.

Following the results of Chapter 2 and 3, then in Chapter 4, I further check the role of reputable CRAs in reducing the financing cost of bond issuers. It is found that hiring reputable CRAs can save bond issuing spread for issuers and this certification effect is reinforced by the entry of CCR, further reflecting its role to discipline the rating behaviour of incumbent CRAs.

1.5.1 Main Findings

1.4.1.1 The Entry of China Credit Rating Improved Information Quality of Ratings on the Bond Market

There were only issuer-pay CRAs' ratings on the market before 2012. Issuers paid for the rating agencies, investors acquired the credit information of bonds mainly through issuer-pay CRAs and the government indirectly supervised the CRAs. Therefore, issuer-pay CRAs had the information advantage of their clients over other participants in the market. Based on the studies discussed in Section 1.1.2, issuer-pay CRAs had an incentive to hide unfavourable issuer information (i.e., rating inflation and reluctance to downgrade ratings), potentially creating information asymmetry between issuers, investors and the government. This study proposes that the entry of CCR revealed more information to the market through its ratings that reduced the information asymmetry to some extent. As information became more transparent, incumbent issuer-pay CRAs had to adjust their rating strategy, thus indirectly improving their rating information quality.

Specifically, this study uses two measurements to represent the rating quality change: rating change level (Chapter 2) and information content of ratings (Chapter 3).

Chapter 2 compares the difference in rating change of CCR-covered firms and uncovered firms. If CCR does reveal more accurate information, it should be observed that the rating inflation level is relatively lower for the CCR-covered sample than the uncovered sample. The DID approach is applied to explore this further. A significantly negative difference is found between the treatment group (covered by CCR) and the control group (not covered by CCR) in terms of the changes in their ratings by incumbent issuer-pay CRAs. This implies that CCR plays a certification role in the credit rating industry; incumbent issuer-pay CRAs adjusted their ratings to the ‘benchmark’ ratings provided by CCR, reducing the severity of the rating inflation and reflecting their improvement of rating’s information quality. Additionally, the sample selection bias is taken into consideration. The propensity score matching (PSM) method and Heckman two-stage approach are applied to control the problem of endogeneity.

Chapter 3 uses ratings information content change to show the rating quality change. If CCR can release more information and affect the behaviour of incumbent issuer-pay CRAs, these CRAs should improve their rating quality and timeliness. This in turn increases the information content of their rating change announcements. If so, investors should have a greater response to the rating change announcements of incumbent issuer-pay CRAs after CCR’s coverage initiation. To evaluate this hypothesis, an event study is applied to compare the rating information content of the issuer-pay CRAs in China before and after CCR’s coverage initiation of each given firm. A significant improvement is found in incumbent issuer-pay CRAs’ ratings information content following CCR’s coverage. Rating changes of issuer-pay CRAs incorporate more information and trigger more sensitive market reactions compared to before CCR’s coverage. This study’s empirical method relies on CCR’s coverage initiation as the inception of CCR’s influence on the rating strategies of incumbent issuer-pay CRAs, and the PSM method and instrumental variable (IV) approach are employed to solve the endogeneity problem.

From the analysis of the above two measurements, it is found that CCR’s entry reduced rating inflation and increased the information content of ratings, both of which reflect a reduction in information asymmetry and an improvement of rating quality.

1.4.1.2 Mechanisms through which CCR’s Entry Improved Rating Quality

After evaluating CCR’s role in improving information quality, this study seeks to find the mechanisms through which CCR’s entry influences incumbent issuer-pay CRAs’ behaviour. In Chapters 2 and 3, two channels are found to play important roles: CRAs’ reputation concerns and the investor protection environment.

First, it is found that more reputable incumbent issuer-pay CRAs are more inclined to change their rating strategy after CCR’s coverage than less reputable ones, releasing more accurate and timely information. Therefore, reputable incumbent issuer-pay CRAs experience lower rating inflation after CCR’s entry and the market is more responsive to rating changes made by reputable incumbent CRAs.

Second, it is found that the incumbent CRAs and market react more to issuers who have a better investor protection environment. In other words, for firms that are more exposed to investors, incumbent issuer-pay CRAs are more likely to be concerned with their quality provision following CCR's coverage.

1.4.1.3 Certification Role of Reputable Credit Rating Agencies in China

As the reputational mechanism can be elevated by the entry of CCR and the ratings given by reputable CRAs experience relatively lower inflation, this study further analyses how the reputation of issuer-pay CRAs certifies the bonds and whether this certification effect is influenced by CCR's entry.

Chapter 4 first analyses the certification hypothesis from the issuer's point of view by asking whether certification from reputable CRAs benefits issuers in China's bond market. In this chapter, issuance data from 2006 to 2015 is employed. After controlling the issuer-CRA selection bias, it is found that reputable CRAs obtain lower bond yields for their clients. In addition, the investor protection environment and issuer's risk are two mechanisms through which the certification effect has influence. Second, the study analyses whether CCR's entry affects the reputation concerns of existing reputable issuer-pay CRAs. It is found that bonds rated by reputable CRAs obtain lower bond yields after CCR's entry and that the certification effect in reducing debt costs by reputable CRAs is stronger for uncovered issuers than CCR-covered issuers.

The findings in Chapter 4 suggest that CRAs' rating decisions reflect reputation concerns and are thus informative of issue quality. Investors take reputable CRAs' ratings as a positive signal and assign a lower yield for issuers. This effect is reinforced by the entry of an independent CRA, verifying the reputational mechanism from another perspective.

1.5.2 Contributions

This thesis contributes to a growing body of literature that examines how different business models of CRA affect credit ratings. The global financial crisis has boosted a surge of research interest in CRAs, particularly in relation to making regulatory reforms in the industry, alleviating the conflicts of interest and relieving the problem of severe rating inflation. While it is not realistic to remove the current issuer-pay business model, many researchers and policy-makers, such as SEC and European financial authorities, have presented proposals to modify the business model. This thesis analyses the influence of launching an independent CRA with a new business model in China and supplements the existing theoretical models, empirical studies and government proposals.

The findings also complement the study on the reputational mechanism by Becker and Milbourn (2011). They identified that the entry of Fitch, another issuer-pay CRA, weakened the incentive of incumbent issuer-pay CRAs to improve rating quality because Fitch induced competition. CCR, which collects money from investors and is supported by the government, does not constitute direct competition. Instead, CCR generates more informative ratings that reveal the low quality of the ratings by incumbent issuer-pay CRAs, subsequently triggering reputation concerns. Xia's (2013) findings suggested that the entry of an investor-pay CRA could elevate the reputational mechanism of S&P and increase the rating quality of incumbent issuer-pay CRAs. This study's findings complement Xia's findings and further show that reputable incumbent CRAs care more about their reputation than do non-reputable ones; thus, the reputational mechanism that increases rating quality works for reputable issuer-pay CRAs. This study's findings also call for investors' attention to the different reactions of different issuer-pay CRAs and emphasise the importance of investor protection environment construction.

This study also supplements the research on the certification effect of CRAs and provides an insight for bond issuers and investors when evaluating bonds rated by CRAs with different reputations.

Xia's (2013) study is the closest to this study in that it focuses on how the rating initiation of an investor-pay CRA—EJR—affects the rating quality of S&P. The author concluded that S&P is more responsive to credit risk and its rating changes contain greater information content after EJR's coverage. In general, S&P improves its rating quality when facing competition from an investor-pay CRA, with this change due to the reputation concerns elevated by EJR's coverage. Xia's (2013) study differs from this study in several important ways. First, EJR is a pure investor-pay CRA and thus different from the independent CRA (CCR) in China, which combine the investor-pay and public utility models. Second, this study not only focuses on the reaction of one specific CRA, but also summarises the general reaction of all incumbent issuer-pay CRAs in China.

The remainder of this thesis proceeds as follows: Chapter 2 estimates the comparison of rating changes between CCR-covered and uncovered groups using the DID approach. Chapter 3 analyses the market reaction to rating change announcements before and after CCR's coverage initiation using an event study. Chapter 4 estimates the certification effect through the reputation of CRAs and how CCR's entry changed this effect. Chapter 5 provides a conclusion to the thesis.

Chapter 2

Reaction on credit ratings as a response to the Entry of CCR

This chapter analyses the role of CCR's entry from the perspective of discipline rating inflation that increases ratings' information quality. Section 2.1 provides a review of this chapter and the related literatures. Section 2.2 includes a description of the data and methodology. Baseline empirical results are presented in Section 2.3 and mechanisms are discussed in Section 2.4. Sections 2.5 and 2.6 are the robustness check analysis and conclusion respectively.

2.1 Introduction

This chapter supplements a growing body of literature that examines how different business models of CRA affect credit ratings. This chapter proposes that the entry of this independent CRA reveals more information to the market through its ratings and reduces the information asymmetry to some extent. As information becomes more transparent, incumbent issuer-pay CRAs have to adjust their rating strategy and become more conservative.

Specifically, I use rating change levels to represent the rating strategy change. I find that the ratings of issuer-pay CRAs have increased during the last 10 years in China and that ratings given by CCR are all lower than issuer-pay CRAs' ratings. Comparatively, the ratings of issuer-pay CRAs are inflated. If CCR does reveal more accurate information, it should be observed that the rating inflation level is lower for the CCR-covered sample then the uncovered sample. I apply the DID approach to estimate if the rating inflation is relatively controlled for the companies covered by the independent CRA, compared with their counterparts that are not rated by this independent CRA. I find a significantly negative difference between the treatment group (covered by CCR) and the control group (not covered by CCR) in terms of the rating changes given by incumbent issuer-pay CRAs. This implies that the independent CRA plays a certification role in the credit rating industry; incumbent issuer-pay CRAs adjust their ratings to the 'benchmark' ratings provided by CCR, increasing their rating quality and reducing the severity of the rating inflation. Additionally, the PSM method and Heckman two-stage approach are applied to solve the problem of endogeneity.

Further, I identify through which mechanisms CCR's entry influences incumbent issuer-pay CRAs' behaviour. Two channels are found to play important roles: CRAs' reputation concerns and the investor protection environment. First, this research finds that more reputable incumbent CRAs are more inclined to change their rating strategy after CCR's coverage than less reputable ones, releasing more accurate and timely information. Therefore, reputable incumbent CRAs experience lower rating inflation for covered firms after CCR's entry. This finding complements the study on the reputational mechanism by Becker and Milbourn (2011). Xia's (2013) findings also suggested that the entry of an investor-pay CRA can elevate the reputational mechanism of S&P and increase the rating quality of incumbent issuer-pay CRAs. The findings complement this and further show that reputable incumbent CRAs care more about their reputation than non-reputable ones; thus, the reputational mechanism that can increase rating quality works for reputable issuer-pay CRAs. The findings also shed light on investors' attention to the different reactions of issuer-pay CRAs. Second, I find that incumbent CRAs react more to issuers who have a better investor protection environment. In other words, for firms that are more exposed to investors, incumbent issuer-pay CRAs are more likely to be concerned with their quality provision following CCR's coverage. This finding sheds light on the importance of market building to which regulatory institutions pay considerable attention.

2.1.1 Related literatures

Under the prevailing issuer-pay model, the principal revenue stream of CRAs is collected from the clients who aim to issue bonds. As a result, CRAs have the incentives to allocate more favourable ratings to customers who have larger issues (Bolton et al., 2012; He et al., 2011) or who are repeated issuers (Bolton et al., 2012). If issuers and issuer-pay CRAs create an information barrier between them and other participants in the bond market, they can take advantages of other counterparties. In turn, if this information asymmetry problem is severe, it would trigger overoptimistic credit ratings and lower the information content of rating change announcements. Due to this concern, the Dodd-Frank Act in 2010 required an assessment of the conflict of interest of issuer-pay CRAs by the Office of the Controller General.

As a response to the information asymmetry problem driven by the issuer-pay CRAs, regulators and researchers have proposed several alternative business models aiming to improve the credit rating qualities. First, an investor-pay business model is recommended since it provides more accurate and timely information, compared to the issuer-pay model (Beaver et al., 2006; Cornaggia and Cornaggia, 2013; Kashyap and Kovrijnykh, 2016; Pagano and Volpin, 2010). Another is an investor-produced model in which the rating agencies are also the end-users of ratings (Becker and Opp, 2013; Bongaerts, 2014). In another dimension of the public utility model, Diomande et al. (2009) and Lynch (2010) advocate for a non-profit public rating agency in the US, arguing that the conflict of interest can be managed by modelling on other successful public independent bodies, such as the Federal Reserve or the Supreme Court. The European Commission Consultative Paper also proposes to create a public European CRA. Finally, there is a platform model proposed by Mathis et al. (2009) and Richardson and White (2009) to prevent the issuer from influencing ratings by setting a platform as an intermediary between issuers and CRAs. The platform is responsible to assign the rating request to a CRA, either randomly or based on CRA's rating quality. The 'Franken Amendment' in the US suggests that for structured products, SEC should introduce a platform to bring all Nationally Recognized Statistical Rating Organizations (NRSROS) and issuers together through an independent organization.

Although the above models have been proposed, there are rare experiments on these models in practice. Furthermore, the weaknesses of other alternative business models aforementioned have been warned. For instance, it has been warned that the free-rider problem would be the main challenge for the investor-pay model (Fennell and Medvedev, 2011; Richardson and White, 2009) and there is still pressure from investors to require inflated ratings (Pagano and Volpin, 2010). In contrast, the investor-produced model is accused of that investors themselves may become the party benefiting most from rating inflation, in terms of lower capital charge (Gonzalez et al., 2011; Sy, 2009). The model developed by Becker and Opp (2013) shows that if running under the existence of issuer-pay CRAs, the investor-produced ratings would be slightly more inflated. At the same time, it is also argued that the public utility model cannot completely wipe off the conflict of interest because the government is also an issuer by its own. It is worried that the public CRA would be biased to the sovereign or municipal bonds, or large companies owned by the government (Cinquegrana, 2009). Another concern for the public utility model is whether the rating quality will decline due to insufficient budgets. The platform model is questioned as well, as it is hard to decide which criteria to use to choose one CRA over another for a rating request.

Different from the above failed experiments, as an attempt to discipline the existing incumbent issuer-pay CRAs, China introduced an independent CRA which is called CCR. An important feature of CCR is that it combines an investor-pay and a public utility model. This unique feature of CCR potentially prevents it from being influenced by both issuers and investors, and at the same time, overcomes the drawbacks of the public utility model as well. The introduction of CCR in China offers a unique setting to test the efficiency and effectiveness of the combination of investor-pay and public utility model.

This study provides fresh insight into the recent debate on the credit rating business models. Jiang et al. (2012) found that the ratings of S&P were higher after it adopted an issuer-pay model, suggesting that the issuer-pay model leads to rating inflation. Xia (2013) documents that the entry of an investor-pay CRA can elevate the reputation mechanism of S&P, then increasing rating quality of incumbents. Our findings suggest that a combined investor-pay and public utility model enhances the information quality of the incumbent issuer-pay CRAs. Our study also adds to prior credit rating business model literature in two dimensions. First, Jiang et al. (2012) and Xia (2013) simply compares between an issuer-pay and an investor-pay models. The new CBR combines an investor-pay model and a public utility model, of which can simultaneously reduce both the conflict of interest problem in the issuer-pay model and the free-rider problem in the investor-pay model. Second, Jiang et al. (2012) and Xia (2013) both use only one incumbent CRA for comparison purpose. This leads to a potential identification concern, that is, the reaction of this particular incumbent CRA may be unrelated to the entry of a new business model, but is due to the reactions to structure change of other incumbent CRAs (e.g., more competition). In contrast, we cover all the incumbent CRAs in the Chinese market in this paper, alleviating this concern substantially.

2.2 Sample and Methodology

Data was collected from Wind, ChinaBond and CCR. Each observation in my sample is an issuer credit rating corresponding to a certain rating action from incumbent issuer-pay CRAs, including a new rating assignment, affirmation, upgrade and downgrade. The sample consists of 17,516 firm–year–CRA observations from 1,534 firms who have rating records for both pre-2012 and post-2012 periods. There are 645 firms covered by CCR for this sample. I included all the long-term issuer credit ratings of Chinese firms assigned by all issuer-pay CRAs. The ratings include both initial ratings and follow-up ratings on an ongoing basis. The study period is from 2006 to 2015 and the data sample excludes ratings for financial institutions, treasury bonds and enterprise set bonds and other non-rated or small volume bond categories. Following the literature, a numerical value is assigned to the ratings as follows: AAA, AAA– = 5; AA+, AA = 4; AA– = 3; A+ = 2; others = 1. There are both practical and theoretical reasons for why I classify the ratings in this way (see Appendix 2.1).

To identify the effect of CCR's entry on the rating inflation of incumbent issuer-pay CRAs I conceived the entry of CCR as an exogenous reform. I am interested in whether the new entrant makes incumbent CRAs more conservative when giving ratings. The default treatment group thus consists of firms covered by CCR. I consider the beginning of 2012 as the start of the treatment as incumbent CRAs reacted to CCR's entry only after CCR officially initiated a number of ratings on the market.

It is observed that there are significant differences in the main financial characteristics between the treatment and control groups (see Table 2.1). There is a possibility that larger firms are more exposed to the market and, consequently, their information is more accessible. Thus, the CCR coverage is inclined to choose those big firms, although its own policy is random choice. Therefore, the assignment into treatment and control groups is not totally random as a true experiment would require. However, for a quasi-experiment, it is sufficient that CCR's entry (a reform dominated by government) can be thought of as if it was randomly assigned into treatment and control groups.

I applied the DID approach to estimate the influence of CCR's entry on rating inflation. An industry-fixed-effect ordinary least squares (OLS) regression model following Becker and Milbourn (2011), Jiang, Harris and Xie (2012), Xia (2013) and Baghai, Servaes and Tamayo (2013) is applied:

$$Rating_i = c + \beta_1 CCRcover_i * Post_i + \beta_2 Post_i + \beta_3 CCRcover_i + \beta_4 X_i + \varepsilon_i \qquad (2.1)$$

In Eq. 2.1, *Rating* denotes the numerical values of ratings given by incumbent issuer-pay CRAs; *CCRcover* is a dummy variable that equals one if the rated firm is also covered by CCR, otherwise it is zero; *Post* is also a dummy variable that equals one if the firm–year–CRA observation is from the period after 2012 (when CCR officially started its business), otherwise it is zero; and *X* is a set of firm characteristic controls. X includes *sales*, which is the natural logarithm of sales; *leverage*, which is the ratio of total liability from the balance sheet to total assets; *ROA*, which is the return on assets that represents profitability; *tangibility*, which is the ratio of property, plant and equipment to total assets; *growth*, which is the year-to-year increase of operating income; *cash equivalent*, which is the ratio of cash, tradable assets and receivable over current assets to represent the liquidity; and *industry* and *year* fixed effects, which correspond to industry and year dummies. In this equation, if CCR's entry alleviates the problem of rating inflation, I would expect to see a negative coefficient on the interaction term β1.

Apart from the OLS model, I also used the ordinal regression model (ORM) to estimate the rating change. In OLS regression, the difference between the nearby rating categories is assumed to be the same. I applied the ORM to avoid this assumption. ORM is commonly presented as a latent-variable model. Defining y* as a latent variable ranging from $-\infty\ to\ \infty$, the structural model is:

$$y^* = \boldsymbol{x_i}\boldsymbol{\beta} + \varepsilon_i$$

I divided y* into J ordinal categories:

$$y_i = m\ if\ \tau_{m-1} \leq y_i^* < \tau_m\ for\ m = 1\ to\ J$$

where the cutpoints $\tau_1$through $\tau_{J-1}$are estimated. Thus, when the latent y* crosses a cutpoint, the observed category changes. Puhani (2012) stated that the treatment effect has the same sign as the coefficient of the interaction term in a DID analysis when using the ORM. The result in Table 2.2 shows that ORM estimation is consistent with estimations using OLS, meaning that the probability of a higher rating for CCR-covered firms decreased after CCR's entry compared to uncovered firms. To better interpret the meaning of the results and analyse the mechanism behind the results, I will mainly focus on the OLS model.

2.2.1 Endogeneity Concerns

Although CCR announced that its coverage is randomly selected, we still observe some shared features among covered firms from Table 2.1. On average, covered firms are significantly different from uncovered firms. This may cause endogeneity problems in econometric analyses investigations, as the role of CCR's entry leads to lower rating inflation in the form of omitted variable bias due to self-selection. If firms' financial characteristics alone are sufficient to cause incumbent issuer-pay CRAs to adjust their ratings regardless of CCR's coverage, the effect of CCR will be overestimated.

To correct this problem, this research addressed the well-recognised issue of endogenous matching in the Heckman (1980) two-stage 'treatment effects' approach in the manner of Ross (2010), Andres, Betzer and Limbach (2014) and Schenone (2004). This approach uses a first-stage equation to determine the probability that the potential endogenous dummy variable equals one and adjusts the sample moments of second-stage multivariate regression to produce unbiased estimates. This thesis estimated the selection equations for firms' characteristics which lead to CCR's coverage in the first stage of Heckman approach. And in the first-stage regression, at least some of the independent variables should be valid instruments in the sense that they are not only meaningful predictors of the likelihood that *CCRcover* equals one, but also independent of the issuer's credit rating and thus properly excludable from the second-stage regression. I argue that issuer's ownership and whether the issuer is a listed firm can serve as the basis for constructing such instruments. *Ownership* equals one if the firm is owned by the government, otherwise it equals zero; *listed* equals one if the firm is listed on the Shanghai or Shenzhen exchange market. According to Livingston et.al (2017), Chinese state-owned-enterprises (SOEs) have easier access to bank loans and receive favorable loan terms. Given the perceived government backing of SOEs, particularly those of the central government, I expect the type of issuer ownership would significantly affect the bond ratings. As SOEs have more exposure to the bond market, the ownership of issuers might be significantly related to the coverage decision of CCR as they have more accessible information on the market. The listing status also has influence on the CCR's coverage decision as issuers with publicly traded equity are likely have more public information, and it will indirectly affect the ratings (Chen and Guo 2010). However, on the contrary, *it is impossible that credit ratings lead to the change of issuers' ownership or listed status (Pagano et al 1998.* Column 4 of Table 2.2 presents the underlying *CCRcover*-issuer matching equation for the rating data. *Ownership* and *listed* are highly statistically significant, confirming the existence of selection bias. From this regression, I then constructed an inverse Mills ratio that is added as a control variable in the second-stage regression. This procedure, suggested by Heckman (1980), corrects the omitted variable (or self-selection) bias caused by endogenous matching. I applied the DID analysis using Eq. 2.2, which adds the inverse Mills ratio to Eq. 2.1, to see if, after controlling the sample selection bias, the entry of CCR alleviates rating inflation.

$$Rating_i = c + \beta_1 CCRcover_i * Post_i + \beta_2 Post_i + \beta_3 CCRcover_i + \beta_4 X_i + \beta_4 Inverse\ Mills\ ratio_i + \varepsilon_i \tag{2.2}$$

Second, I applied the PSM approach (Xia 2013). I matched CCR-covered firms in the sample (treated group) to those not rated by CCR as of the end of 2015 (control group) based on various dimensions that are likely to predict CCR's coverage decision. The aim is that putting together firms (firm–year–CRA) that are similar in these dimensions will allow us to obtain matched firm–year–CRA observations that designate when CCR would have begun to rate the firm had it decided to cover the firm. The thesis matched the sample firms based on a set of pre-treated (i.e., one year prior to CCR coverage) characteristics and used one-to-one matching method to match each year. The propensity score matching (PSM) approach pairs treatment and control firms based on similar observable characteristics (Dehejia and Wahba, 2002). In particular, I match CCR covered (or rated) firms in the sample (the treated group) to those not rated by CCR (the control group) based on a set of firm characteristics of CRAs, including size, leverage, ROA, operating income growth rate, tangibility, and cash ratio. The idea is that, by putting together firm-year-CRAs that are similar in these dimensions, we obtain matched firm-year-CRAs that designates when CBR would have begun to rate the firm had it decided to cover the firm. Following the suggestion of Roberts and Whited (2012), we use PSM with replacements which allows a given untreated observation to be included in more than one matched set. This procedure ensures a proper identification as it allows for better matches and less bias, and alleviates the sensitivity of the estimated effect towards the order in which the treatment observations are matched. These matched firms are the most similar ones to the covered sample. From the control group, I found 389 matching firms in the treatment group. Through the regression results using the PSM sample, we can observe a much clearer effect of CCR's entry, supposing that the treatment and control groups are similar in terms of the chosen dimensions.

2.3 Empirical Results

2.3.1 Descriptive Statistics

Table 2.1 presents the characteristics of all firms who received ratings by the nine incumbent issuer-pay CRAs between 2006 and 2015. Of the total 17,516 ratings assigned to these firms by the issuer-pay CRAs, the mean rating is 3.991, meaning that the long-term rating is, on average, AA to AA+.

Next, I compared the characteristics of treatment and control groups. Panel B of Table 2.1 presents summary statistics for the control group and treatment group respectively. We can observe that the mean rating and median rating of the treatment group are both significantly higher than the control group. Further, their financial characteristics are significantly different from each other. For example, the mean rating perceived by firms who are covered by CCR is (0.518 notches) higher, and the leverage of firms in the treatment group is significantly (7.361%) higher than the control group. According to CCR's internal policy, it chooses the covered firm on a random basis.[19] However, from Panel B of Table 2.1 it can be seen that, on average, firms from the covered group (treatment group) have a larger size, higher leverage level, higher proportion of tangible assets and lower growth rate.

2.3.2 Baseline Empirical Results

Table 2.2 presents the regression results for Eq. 2.1 and Eq. 2.2. In Columns 1 to 3 of Table 2.2 we test the raw sample that includes 17,516 firm–year–CRA observations, with and without industry and year fixed effects respectively. The negative correlation between incumbent issuer-pay CRAs' ratings and the interaction term suggests that, overall, ratings for treated firms are relatively lower than controlled firms after the entry of CCR, which is significant at a 1% significance level. In other words, CCR's entry has had a significant influence on alleviating the rating inflation problem of the issuer-pay CRAs in China, reflecting the improvement of rating quality. For example, in Column 3 the coefficient of β_1 is –0.097, significant at 1% significance level. This means that, compared with CCR-uncovered firms, the rating inflation for CCR-covered firms is 0.097 notches lower.

Other control variables also show expected signs. For example, ratings are higher for the post-period, which is in line with previous studies on rating inflation in China's bond market (Kennedy 2003, 2008; Lee 2006; Song 2013). Overall, covered firms have higher ratings than uncovered firms, which is consistent with the data description in Table 2.1. This research also finds larger sales, more tangibility and a higher growth rate are all associated with a more favourable rating, while a higher leverage ratio leads to a lower rating.

[19] Interview with the insiders of CCR.

Column 4 of Table 2.2 is the probit regression result of the Heckman first-stage sample selection bias method. Whether CCR covers a specific firm or not is highly related to the financial characteristics of that firm. For example, firms with larger size and state ownership are more likely to be covered by CCR. Columns 5 to 7 report the second-stage regression results of the Heckman test with industry or year fixed effects and the results of Eq. 2.2. I still observe a negative value of β_1, which means that after correcting the sample selection bias, the entry of CCR still significantly alleviates the rating inflation for the covered group. Columns 8 to 10 present the results of Eq. 2.1 when applying the PSM sample—the results still hold. The results from the ORM is represented in Column 11, and we also find a negative value for the coefficient of the interaction term.

This implies that the rating given by CCR has a benchmark effect for other incumbent issuer-pay CRAs, elevating some mechanisms which lead incumbent CRAs to give more conservative ratings. This demonstrates that ratings of CCR add private information to the market, thereby alleviating the information asymmetric problem and improving the rating quality to some extent.

Table 2.1: Rating Sample Summary Statistics

Table 2.1 presents descriptive statistics for the rating sample from 2006 to 2015. The firms in the sample have been rated both before and after the official entry of CCR. Panel A presents the statistics of the full sample. *Rating* is a numerical value given by the issuer-pay CRAs, based on a notch basis as follows: AAA, AAA– =5; AA+, AA = 5; AA– = 3; A+ = 2; others = 1; *post* is a dummy variable that equals one if a firm–year–CRA observation is from the period after 2012, and zero otherwise; *CCRcover* is a dummy variable that equals one if a firm was rated by CCR at any time, and zero otherwise; *sales* are the natural log of total sales; *leverage* is the ratio of total liability from the balance sheet to total assets; *ROA* is the return on assets that represents the profitability; *tangibility* is the ratio of property, plant and equipment to total assets; *growth* is the year-to-year increase of operating income; *cash equivalent* which is the ratio of cash, tradable asset and receivable over current asset; all above variables are measured at the time t-1. Panel B presents the statistics of the controlled group and treatment group and the mean differences between these two groups. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels respectively.

Panel A: Summary statistics of full sample										
		Rating	Post	CCRcover	Sales	Leverage	ROA	Tangibility	Growth	Cash equivalent
Whole sample	N	17,516	17,516	17,516	17,457	17,470	17,466	17,460	17,406	17,467
	Mean	3.991	0.652	0.571	4.432	60.097	0.521	0.259	0.653	0.470
	Std.dev.	0.790	0.476	0.495	1.864	15.083	1.214	0.202	12.365	1.013
	Min.	1	0	0	–4.605	0.300	–6.578	0	–0.989	0
	Max.	5	1	1	10.268	162.200	86.112	0.969	645.822	100.018
Panel B: Summary statistics of the controlled group and treatment group										
Firms not covered by CCR	N	7522			7473	7487	7483	7479	7436	7486
	Mean	3.696			3.454	55.891	0.446	0.203	1.221	0.540
	Std.dev.	0.793			1.661	15.812	0.494	0.181	18.889	1.470
	Min.	1			–4.605	0.300	–6.578	0	–0.989	0.009
	Max.	5			8.437	162.200	6.300	0.961	645.822	100.018
Firms covered by CCR	N	9994			9984	9983	9983	9981	9970	9981
	Mean	4.214			5.164	63.252	0.578	0.301	0.229	0.417
	Std.dev.	0.711			1.659	13.690	1.545	0.207	0.662	0.411
	Min.	1			–2.303	6.840	–4.072	0	–0.833	0
	Max.	5			10.268	139.850	86.112	0.969	23.685	13.884
Mean difference		0.518***			1.711***	7.361***	0.132***	0.098***	–0.992***	–0.123***
Median difference		0***			1.688***	8.150***	1.121***	0.107***	0.008*	–0.048***

Table 2.2: Difference-In-Differences Analysis of Ratings

Table 2.2 presents the DID analysis results for the raw sample, Heckman sample and PSM matched sample from 2006 to 2015. The raw sample and Heckman sample consist of 17,389 firm–year–CRA observations of 1534 firms from 2006 to 2015. Columns 1, 2 and 3 represent the regression results of Eq. 2.1. The left-hand-side variable is the cardinal value of credit ratings. All the variables are the same as in Table 2.1. Firm fixed effects are indicator variables for firms; year fixed effects are indicator variables for fiscal years. Columns 4 to 7 present the DID result using the Heckman test to correct the sample selection bias. Column 4 presents results of the probit regression of CCR's coverage choice on firm-specific characteristics for the sample of ratings given by issuer-pay CRAs between 2006 and 2015. The left-hand-side variable is CCRcover. Ownership equals one if the firm is owned by the government, otherwise zero. Columns 5 to7 present the regression results of Eq. 2.2. Columns 8 to 10 present the DID results using PSM sample. Column 11 presents the result applying ORM. The firms in these samples all have ratings both before and after the entry of CCR. Industry fixed effects are indicator variables for firms; year dummies are indicator variables for fiscal years. Standard errors are in the parentheses. R-squared is reported. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels respectively.

	Raw sample			Heckman sample				PSM matched sample			ORM
	(1)	(2)	(3)	(4) First stage	(5)	(6)	(7)	(8)	(9)	(10)	(11)
CCRcover*Post	–0.150***	–0.110***	–0.097***		–0.122***	–0.112***	–0.096***	–0.074***	–0.074***	–0.059***	–0.229***
	(0.024)	(0.021)	(0.019)		(0.022)	(0.021)	(0.019)	(0.025)	(0.024)	(0.022)	(0.068)
CCRcover	0.624***	0.273***	0.259***		0.316***	0.275***	0.255***	0.236***	0.235***	0.194***	0.748***
	(0.019)	(0.018)	(0.016)		(0.019)	(0.018)	(0.016)	(0.020)	(0.019)	(0.018)	(0.059)
Post	0.331***	0.280***			0.298***	0.282***		0.248***			0.720***
	(0.018)	(0.016)			(0.017)	(0.016)		(0.021)			(0.052)
Sales		0.227***	0.264***	0.335***		0.231***	0.244***	0.255***	0.254***	0.283***	0.870***
		(0.003)	(0.003)	(0.008)		(0.009)	(0.008)	(0.004)	(0.003)	(0.003)	(0.014)
Leverage		–0.010***	–0.010***	0.005***		–0.010***	–0.010***	–0.010***	–0.010***	–0.010***	–0.038***
		(0.000)	(0.000)	(0.001)		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
ROA		–0.008*	0.003	0.269***		–0.007*	0.000	–0.004	–0.002	0.002	–0.301***
		(0.004)	(0.004)	(0.026)		(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.041)
Tangibility		0.091***	0.011	1.030***		0.102***	-0.054	0.277***	0.321***	0.051*	0.641***
		(0.025)	(0.028)	(0.055)		(0.035)	(0.036)	(0.026)	(0.026)	(0.029)	(0.084)
Growth		0.001***	0.001**	-0.030***		0.004**	0.005***	0.008**	0.009***	0.003	0.004***
		(0.000)	(0.000)	(0.009)		(0.002)	(0.001)	(0.003)	(0.003)	(0.003)	(0.001)
Cash equivalent		0.037***	0.032***	0.008		0.037***	0.031***	0.079***	0.073***	0.068***	0.192***
		(0.005)	(0.004)	(0.011)		(0.005)	(0.004)	(0.009)	(0.009)	(0.008)	(0.028)
Ownership				0.156***							
				(0.028)							

Listed				–0.145***							
				(0.025)							
Inverse Mill ratio					–0.638***	0.017	–0.112***				
					(0.013)	(0.043)	(0.039)				
Constant	3.474***	3.256***	2.800***	-2.045***	4.132***	3.220***	3.011***	3.045***	2.457***	2.781***	
	(0.015)	(0.025)	(0.063)	(0.061)	(0.019)	(0.085)	(0.097)	(0.033)	(0.068)	(0.064)	
Observations	17,516	17,388	17,388	17,388	17,381	17,381	17,381	13,511	13,511	13,511	17,388
Prob (Chi-squared)				0.000							0.000
(Pseudo) R-squared	0.129	0.322	0.452	0.196	0.233	0.322	0.452	0.337	0.366	0.471	0.206
Industry fixed effects	No	No	Yes	No	No	No	Yes	No	No	Yes	No
Year dummies	No	No	Yes	No	No	No	Yes	No	Yes	Yes	No

2.4 Analyses Conditional on Reputational Differences and the Investor Protection Environment

As aforementioned, this research proposes that there are two mechanisms through which the CCR's entry can alleviate rating inflation and discipline the behaviour of incumbent issuer-pay CRAs. The mechanisms are reputation concerns and the investor protection environment.

2.4.1 The Effect of China Credit Rating's Coverage Initiation Conditional on Reputational Differences among Issuer-Pay Credit Rating Agencies

The alleviation of rating inflation might reflect a reputational mechanism at work. That is, CCR's independent and more conservative ratings have elevated the reputation concerns of the more reputable issuer-pay CRAs, who subsequently strengthen their incentives to lower the rating inflation (the 'incentive/reputation' channel). Specifically, when CCR covers a firm, its lower ratings reveal the low quality of the ratings from issuer-pay CRAs as discussed in Chapter 1. This eventually either lowers investors' confidence in incumbent issuer-pay CRAs, making them less valuable to issuers, or leads to closer scrutiny and intervention from regulators. The fear of reputation cost provides a mechanism through which CCR's entry can discipline issuer-pay CRAs into providing a lower rating inflation (Bar-Isaac & Shapiro 2013; Bolton, Freixas & Shapiro 2012; Mathis, McAndrews & Rochet 2009; Opp, Opp & Harris 2013; Skreta & Veldkamp 2009).

However, in China, the reputation of issuer-pay CRAs is criticised (Kennedy 2008; Lee 2006). Specifically, Bottelier (2003) found that most listed CBs in China have AAA ratings. According to the qualitative research of Xu and Han (2013), the credit rating industry in China is thought to be immature, the reputation of China's CRAs is low, rating results lack fairness and severe competition dominates the market. Others contend that from the beginning, China's CRAs have earned money from issues rather than investors, while their US counterparts collected revenue from investors for about 70 years, during which time they built up their reputation, before changing to an issuer-pay model. Thus, it is argued that China's CRAs need a longer time to mature (Poon & Chan 2008). Zhang and Zhang (2010) and Zhang (2013) all built models to prove the effects of the reputational mechanism under certain contexts in China and offered policy suggestions such as decreasing competition. It is believed that there are quality differences among issuer-pay CRAs in China. Therefore, this research aims to find out whether the influence of CCR's entry stems from the difference in reputation concerns between reputable issuer-pay CRAs and non-reputable CRAs.

In order to test the above assumption, I divided all issuer-pay CRAs into two groups: reputable and non-reputable. The reputable group consisted of CCXI and Lianhe, while the non-reputable group comprised of the others. The CRAs were sorted into the two groups based on three criteria. First, according to previous studies on the reputation of other financial intermediaries, such as underwriters and banks, market share is a widely used criterion (Andres, Betzer & Limbach 2014; Megginson & Weiss 1991; Schenone 2004). Appendix 2.1 shows the market share of each issuer-pay CRA based on the issue volume and number of bonds they rated between 2006 and 2015. CCXI and Lianhe accounted for over 70% of the market and are the top two issuer-pay CRAs in China in terms of market share.

Second, as shown in previous studies, international CRAs have a better reputation than national CRAs. Thus, the second criterion is whether the issuer-pay CRA has foreign ownership—namely the big three: Moody's, S&P and Fitch. The big three are long-established global rating agencies (GRAs) and are generally have a greater advantage when competing with national rating agencies (NRAs). GRAs enjoy superior market power mainly due to their reputation capital (Hill 2004; Partnoy 1999). As NRAs lack a well-established reputation, investors are more likely to trust the ratings issued by GRAs whose reputation is at stake. Additionally, GRAs are thought to hold a higher level of independence. Empirical studies comparing GRAs and NRAs mainly focus on the Japanese market—the world's second largest bond market with the most well known NRAs. Some of these studies provide evidence in support of the superiority of GRAs. For example, Beattie and Searle (1992) suggested that CRAs are inclined to be more lenient when judging issuers from their own countries, raising doubts about their integrity and credibility. Cantor and Packer (1997) suggested that Moody's and S&P assign lower ratings than smaller CRAs. From a sample of Japanese non-financial companies, Packer (2002) found evidence that, on average, NRAs' ratings are systematically 3.5 notches higher than GRAs' ratings. Shin and Moore (2003) showed the inflated natures of NRAs in Japan, while Nickell, Perraudin and Varotto (2000) suggested that NRAs are slower in downgrading compared with GRAs. Additionally, Carow (1999) and Li, Shin and Moore (2006) advocated the superiority of GRAs by showing that GRAs have more influence on the Japanese capital market than NRAs. As mentioned in Chapter 1, there are two joint venture CRAs in China: CCXI (in which Moody's has a 49% stake) and Lianhe (in which Fitch has a 49% stake). Moody's and Fitch not only provide advanced rating techniques for their affiliates, but also assign representatives to participate in the rating decision process. Therefore, according to the second criterion, CCXI and Lianhe should be more independent with higher reputation capital and concern about their long-term reputation.

Third, CRAs in China need to acquire recognition from different supervisors, the most difficult being the qualification from the PBOC and the CIRC. As the PBOC is in charge of the interbank market, the largest trading market in China, recognition from the PBOC means the bonds issued by these CRAs can be traded by almost all market participants. In addition, the CIRC is the regulatory organisation for insurance companies and have the most conservative investment strategy among all financial institutions. Therefore, recognition from the PBOC and the CIRC are essential to CRAs. Both CCXI and Lianhe have this qualification, satisfying the third criterion.

In relation to the three criteria, only CCXI and Lianhe are recognised as reputable issuer-pay CRAs in China. Column 1 of Table 2.3 shows the comparison between the reputable and non-reputable groups. We can observe a significantly negative coefficient for the interaction term at a 1% significance level for the reputable group, which is not found for the non-reputable group. This means that CCR's entry disciplines the rating inflation behaviour for reputable incumbent CRAs; however, it does not have a significant influence on non-reputable issuer-pay CRAs. This is consistent with the literature in that the reputational mechanism can be elevated through competition from a more credible CRA, especially for those who care more about reputation. Moreover, the difference between the coefficients of these two groups is statistically significant. This is also in line with the aforementioned literature that suggests that GRAs are more concerned about their rating quality and long-term reputation than NRAs. In other words, after controlling for the issuer's financial characteristics, when CCR initiates ratings for an issuer that is also covered by a reputable issuer-pay CRA, that CRA will give lower ratings to this issuer in the post-period compared with firms not covered by CCR. This behaviour is significantly different from that of non-reputable CRAs, who are not sensitive to CCR's entry.

2.4.2 The Effect of China Credit Rating's Coverage Initiation Conditional on Issuers' Investor Protection Environment

This study proposes that issuers with a better investor protection environment are likely to be more exposed to the public and attract more attention from investors. These issuers are under stricter scrutiny and supervision from investors and regulators. This, in turn, puts pressure on incumbent issuer-pay CRAs to improve their rating quality following CCR's coverage, because CCR's more informative ratings reveal the low quality of incumbent CRAs' ratings. Therefore, I expect that in the context of issuer-pay CRAs in China, issuers with a better investor protection environment experience lower rating inflation after CCR's coverage.

To test this hypothesis, I performed an analysis conditional on the issuer's investor protection environment. I used two variables to capture the investor protection environment: investor protection index (IPI) and rating frequency.

2.4.2.1 Investor Protection Index

It is commonly accepted that better investor protection is associated with better financial markets (Dahya, Dimitrov & McConnell 2008; La Porta et al. 1997). In China, there are more than 30 provinces with unequal levels of economic development and investor protection. Some highly-developed provinces, such as Guangdong, Zhejiang, Beijing and Shanghai, have a more mature legal system, better investor protection mechanisms and friendlier investment environment. Conversely, other provinces, such as Gansu and Xinjiang, have a relatively incomplete market and legal environment. It is expected that firms from provinces with better investor protection are more exposed to the market and have a better investor protection environment.

The index developed by Porta et al. (1998) is commonly used and includes indicators such as accounting standards, rule of law, anti-director rights and a dummy variable for common-law countries. However, these indicators cannot be directly used in China. The index used in this study was developed by Fan, Wang and Zhu (2011). It is consistent with the work of Porta et al. (1998) and widely applied in the existing literature on China's market (Ayyagari, Demirgüç-Kunt & Maksimovic 2010; Cull & Xu 2005; Fan, Wong & Zhang 2007). The specific index I chose as the proxy of investor protection environment is the index measuring the development of market intermediaries, protection of the legal rights of producers, protection of copyright and protection of consumers.

Therefore, an issuer is classified as having a better investor protection environment if it comes from a province that is above the sample median. The high IPI group consists of firms who come from provinces with an IPI above the median level (otherwise, the company belongs to the low IPI group). Subsequently, I regressed Eq. 2.1 and Eq. 2.2 by using samples from both high and low IPI groups and compared the difference of their coefficients on the interaction term. If a significantly negative value of the difference is observed, it means covered firms with a higher IPI (better investor protection environment) experience lower rating inflation after CCR's entry.

From Column 2 of Table 2.3, I find significant evidence that incumbent issuer-pay CRAs decrease their rating inflation in the treatment group after CCR's entry for the high IPI group, but no clear evidence for the low IP group. The difference between the high and low IPI samples is significant in terms of the coefficient of the interaction term for all three models. This result indicates that in areas with an advanced legal system and better investor protection environment, issuer-pay CRAs are more conservative in their ratings. The reason for this may be that the issuers in these provinces are more sophisticated than other provinces, and have more public information to be accessed on the market. Thus, CRAs need to care more about the loss of reputation capital and the regulatory cost of inflating the ratings for them.

2.4.2.2 Rating Frequency

The rating frequency indicates how often firms are rated by issuer-pay CRAs. It is assumed that the more times a CRA has rated a firm, the closer their relationship with the issuer. As mentioned previously, in the long run, CRAs need to consider their reputation to secure their long-term revenue. Thus, the market has more access to the issuer's information when the issuer is rated frequently. Therefore, I used rating frequency as another proxy for the investor protection environment.

This research hypothesises that for the high-frequency group, issuer-pay CRAs decrease their rating inflation for CCR-covered companies compared with uncovered ones, while there is no such relationship for the low-frequency group. I defined an issuer as having a better investor protection environment if the frequency of ratings it received between

2006 and 2015 is above the sample median of rating frequency[20]. The high-frequency group has a better investor protection environment than did the low-frequency group. From Column 3 of Table 2.3, we observe significant differences (0.115) between the coefficients of interaction terms of the two groups at a 1% confidence level for all models.

In summary, through the analysis of the investor protection environment, this thesis found that issuers with a better investor protection environment experience significant rating inflation reduction after the entry of CCR, while we cannot observe this from firms with worse investor protection environment. This implies that the rating information quality improvement is more pounced for firms having better investor protection environment following the introduction of an independent CRA. This also emphasises the importance of investor protection environment construction in the financial market.

In general, reputable CRAs and firms with a better investor protection environment experience lower rating inflation following CCR's entry, reflecting a reduction in information asymmetry and improvement of rating quality.

[20] The reason of choosing the rating times between 2006 and 2015 rather than between 2006 and 2012 is that the rating behaviour and strategy changes of incumbent CRAs are gradually happened. Along the time, CRAs will keep updating their knowledge on issuers' level of exposure to information. If we only use the data before 2012, we would ignore the dynamic process of rating strategy change of CRAs.

Table 2.3:[21] Difference-In-Differences Analysis of Ratings Categorised by the Reputation of Issuer-Pay Credit Rating Agencies

Table 2.3 presents the DID analysis results categorised by reputation and investor protection environment. The reputable group consists of two CRAs: CCXI and Lianhe. The non-reputable group consists of the other seven issuer-pay CRAs. The high IPI group consists of firms from provinces with a higher-than-median IPI. The high-frequency group consists of firms whose number of ratings between 2006 and 2015 are above the median rating times; otherwise the company belongs to the low-rated frequency group. The *Diff. of. Coefficient* equals the coefficient of CCRcover*Post for reputable group minus that for non-reputable group for column 1; the coefficient of CCRcover*Post for high-IPI group minus that for low-IPI group for column 2; the coefficient of CCRcover*Post for high-frequency group minus that for low-frequency group for column 3, respectively. Industry fixed effects are indicator variables for industry; year dummies are indicator variables for fiscal years. Standard errors are in the parentheses. R-squared is reported. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels respectively.

	(1) Reputation		(2) Investor protection index		(3) Rating frequency	
	Non-reputable	Reputable	Low IPI	High IPI	Low frequency	High frequency
CCRcover*Post	–0.011	–0.171***	–0.032	–0.154***	–0.017	–0.132***
	(0.030)	(0.030)	(0.029)	(0.030)	(0.031)	(0.034)
Diff. of coefficient	–0.160***	chi2 = 13.91	–0.122***	chi2 = 8.52	–0.115**	chi2 = 6.26
CCRcover	0.191***	0.317***	0.226***	0.289***	0.154***	0.158***
	(0.029)	(0.026)	(0.026)	(0.027)	(0.029)	(0.029)
Sales	0.242***	0.280***	0.238***	0.266***	0.283***	0.230***
	(0.006)	(0.005)	(0.007)	(0.005)	(0.007)	(0.005)
Leverage	–0.008***	–0.011***	–0.010***	–0.008***	–0.013***	–0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ROA	0.008	0.004*	0.029	0.003	0.007	0.004***
	(0.026)	(0.002)	(0.024)	(0.002)	(0.022)	(0.001)
Tangibility	0.091**	–0.050	0.043	0.071	–0.040	0.056
	(0.045)	(0.039)	(0.038)	(0.047)	(0.043)	(0.039)
Growth	0.000	0.001***	0.001*	0.001***	0.001**	0.000
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Cash equivalent	0.050***	0.027*	0.023**	0.118***	0.027**	0.157***
	(0.016)	(0.015)	(0.011)	(0.033)	(0.012)	(0.021)
Constant	2.260***	2.952***	2.594***	2.800***	2.781***	2.765***
	(0.205)	(0.098)	(0.151)	(0.123)	(0.176)	(0.116)
Observations	8268	9120	8626	8762	9302	8086
R-squared	0.395	0.493	0.379	0.490	0.356	0.456
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes

[21] From this table on, we will focus on the model with industry and year fixed effects.

2.5 Robustness Check

2.5.1 Marginal Effects from the Ordinal Regression Model

The rating variable can be treated as both continuous and discrete variables, for the convenience of explaining the underlying mechanisms of rating quality change, this thesis threats it as continuous variable. Here, as a robustness check, I treat it as ordinal variable and analyse it using ORM model. I applied the ORM regression using different ways to classify the ratings and analysed the marginal effect for each classification. For all scenarios, we found that the coefficients of the interaction term are significantly negative and the probability of being assigned a higher rating is reduced, while the probability of being assigned a lower rating is increased for the treatment group in the post-period compared with the control group (see Appendix 2.3). The results from ORM are in line with the preliminary results.

2.5.2 Alternative Ratings Classifications

Based on the discussion of classification and regression tree (CART) analysis in Appendix 2.2, I applied the DID regression on four alternative types of rating classifications. I explore whether the results are sensitive to the rating classification (i.e. the dummy variable with 5 grades). To address this concern, I develop four alternative dummy variables measures. The first and second measures are similar to the existing one, where AAA, AAA-=5, AA+=4, AA=3, AA-=2, others=1 and AAA, AAA-=4, AA+, AA=3, AA-=2, others=1, respectively. In the third measure, a numerical value is assigned to the ratings as follows: AAA, AAA-=9, AA+=8, AA=7, AA-=6, A+=5, A=4, A-=3, BBB+=2 and others=1. For the fourth measure, AAA, AAA-=6, AA+=5, AA=4, AA-=3, A+=2, and others=1.The results still hold (see Appendix 2.4).

2.5.3 Alternative Sample Period

This thesis considered the possibility that the influence of CCR's entry may be delayed. Therefore, I deleted the observations in 2012 and assumed that the market needed one year to react to CCR's coverage. The result does not change qualitatively. In addition, it is assumed the experiment was implemented from 2011 and made the *post*-dummy equal one if the observation was after 2011. We do not observe any significant results in the PSM sample (see Appendix 2.5).

2.5.4 Additional Check on Mechanisms Using the Propensity Score Matching Sample

To future correct the potential endogeneity problem, I used the PSM sample to test the reputational mechanism and investor protection environment mechanism found in the DID regression. The results still hold (see Appendix 2.6).

2.5.5 Additional Check on Mechanisms Using the Heckman Sample

Although DID method itself to some extent can cure the potential endogeneity issue, but to further address that the rating quality change of reputable CRAs results from CCR's entrant rather than reputable CRAs' own client's selection bias, Heckman method is employed. It is concerned that CCR's coverage decision may result from its preference to larger and more solvent firms and this selection bias cause the empirical results. Heckman two stage method is thought to good cure to alleviate the above selection bias. I used the Heckman sample to test the reputational mechanism and investor protection environment mechanism found in the DID regression. The results still hold (see Appendix 2.7).

2.5.6 Additional Check on Conditional Regression

As discussed, the reputable issuer-pay CRAs pay more attention to their credibility; thus, they should be more cautious when dealing with ratings for firms that have a better investor protection environment following CCR's coverage. Therefore, for issuers with a better investor protection environment, this thesis assumes that reputable issuer-pay CRAs should experience a greater improvement in their rating information content. The empirical result confirms the prediction (see Appendix 2.8).

2.5.7 Additional Proxy to Measure Investor Protection Environment

I used the Marketization Index (MI) in 2009 (Fan, Wang & Zhu 2011) as a proxy for the investor protection environment. I divided the sample into two groups. The high MI group consists of firms from provinces with a higher MI than the median level; the low MI group comprises firms from provinces with a lower MI than the median level. The empirical result confirms the investor protection environment mechanism (see Appendix 2.9).

2.6 Conclusion

This chapter examined how the entry of CCR, a new independent CRA that utilises a combination of the public utility and investor-pay models, affects the behaviour of incumbent issuer-pay CRAs in China. To be best of this researcher's knowledge, this combined business model is unique in China. I found a decline in rating inflation for those firms covered by CCR compared to those not covered by CCR. This indicates that CCR acts in a certification role to discipline incumbent issuer-pay CRAs, creating a benchmark for them. This also reflects the rating quality of incumbent issuer-pay CRAs has been improved.

In particular, this discipline effect is more significant among the more reputable issuer-pay CRAs and firms with a better investor protection environment. Thus, I further find that reputation and public supervision are two mechanisms through which CCR's entry influences incumbent CRAs' rating behaviour.

The findings in this chapter complement the existing literature that documents a negative link between the entry of a new issuer-pay CRA and incumbent issuer-pay CRAs' rating inflation. These findings also shed light on the debate concerning whether CRAs with alternative business models can alleviate the rating inflation problem. They also generate policy implications regarding the distinct effects of different types of CRAs on existing providers' rating strategies and emphasise the importance of investor protection environment construction.

Chapter 3
Does the Market Care about Rating Change Announcements Following the Entry of a New Player?

This chapter analyses the relationship between CCR's entry and information quality of the incumbent issuer-pay CRAs from the perspective of how investors reacted to incumbent CRAs' rating change announcements following CCR's coverage initiation. Section 3.1 provides a general introduction to the chapter and related literatures. Section 3.2 describes the data collection and descriptive statistics. Methodology and baseline empirical results are shown in Section 3.3. Section 3.4 discusses the IV and PSM methods to remedy the endogeneity problem. Section 3.5 estimates the mechanisms. Sections 3.6 and 3.7 are the robustness test and conclusion respectively.

3.1 Introduction

By investigating the market reaction to the rating change announcements issued by incumbent issuer-pay CRAs before and after CCR's coverage initiation, I find that the rating changes incorporate significantly higher information content after CCR's coverage. This result adds empirical evidence to the literature documenting the influence of introducing a new rating agency with an alternative business model on issuer-pay rating agencies.

I study this implication by comparing the information content of the ratings by issuer-pay CRAs in China before and after CCR's coverage initiation of each given firm. If CCR releases more information that affects the behaviour of incumbent issuer-pay CRAs, then the issuer-pay CRAs should improve their rating quality and timeliness, incorporating more information in their ratings. This, in turn, increases the information content of their rating change announcements. If so, investors should have a greater response to the rating change announcements of incumbent CRAs after CCR's coverage initiation. To investigate this hypothesis, I apply an event study to compare the ratings information content of the issuer-pay CRAs in China before and after CCR's coverage initiation of each given firm. I find a significant improvement in incumbent CRAs' ratings information content following CCR's coverage. Rating changes of issuer-pay CRAs incorporate more information and trigger more sensitive market reactions compared to that before CCR's coverage.

The empirical method relies on CCR’s coverage initiation as the inception of CCR’s influence on the rating strategies of incumbent issuer-pay CRAs. In practice, CCR announced that its coverage is random. However, from the descriptive statistics results, this thesis finds CCR is more likely to cover firms larger in size, and with greater sales and higher tangibility. As a result, CCR’s coverage might not be exogenously determined; CCR might cover a firm because it was concerned that the firm had an inflated rating given by issuer-pay CRAs, or investors were not satisfied with the unresponsiveness of the present ratings. If these concerns simultaneously led incumbent CRAs to adjust their rating quality regardless of CCR’s coverage, then the influence of CCR’s entry on information content might be overestimated.

To remedy this issue, I employ two approaches. First, I apply an IV analysis to build a causal role of CCR’s coverage initiation. The instrument for the timing of CCR’s coverage of each firm is the firm’s one year prior industry average total asset. This instrument can predict CCR’s coverage decisions because CCR is inclined to cover firms with a larger size. However, the industry-level total asset is unlikely to be directly correlated with the rating informativeness of issuer-pay CRAs for a particular firm. Using the IV procedure, the effect of CCR’s coverage on rating information content is at the same magnitude of that estimated in the OLS. This confirms the causal role of CCR’s coverage.

Second, I apply a PSM method and find that the improvement in incumbent CRAs’ rating information content is unique to firms that are actually covered by CCR and is not present for firms with similar characteristics that do not have CCR coverage.

Finally, this chapter also highlights the importance of CRAs’ reputations and investor protection environment on the effect of CCR’s coverage on information content of rating changes by issuer-pay CRAs. This research finds that the market reacts more to rating changes made by reputable incumbent CRAs. Further, I find that the market reacts more to rating changes of issuers who have a better investor protection environment. In other words, incumbent issuer-pay CRAs are more likely to be concerned with their quality provision after CCR’s coverage initiation for firms that are more exposed to investors.

3.1.1 Related literatures

Researchers have used single or multi regression models or event study to test the reaction of stock and bond prices to credit ratings. If the change in price is significantly related to credit ratings regardless of the initial rating or change in rating, the credit ratings are informative and valuable (Barron, Clare & Thomas 1997; Goh & Ederington 1993; Holthausen & Leftwich 1986; Kliger & Sarig 2000; Nayar & Rozeff 1994). It has evidences that both an upgrade and a downgrade in ratings can add information to the bond market, and that the stock market reacts more strongly to a downgrade (May 2010), and May (2010) used OTC market data. This is consistent with the findings of Nayar and Rozeff (1994) and Cantor (2004). Behr and Guttler (2008) confirm this opinion by estimating the influence of unsolicited ratings of S&P on stock price from 1996 to 2005 and conclude that unsolicited ratings also convey new information. Goh and Ederington (1993) further distinguished among different types of downgrade, and they argued that the anticipated ratings changes and downgrades due to wealth transfer from bondholders to stockholders should not cause a significant negative stock response. Galil and Soffer (2011), on the other hand, argue that positive announcements from agencies add more information to the CDS market, controlling the presence of concurrent public and private information. Based on an analysis if the rating data of Moody's from 1982 to 2004, Bannier and Hirsch (2010) have also identified the economic function underlying the watch lists of rating agencies. They give positive assure on CRAs for their active monitoring function. Xia (2013) finds S&P's rating downgrade announcements cause more market reaction following the coverage of the investor-pay EJR.

This study enhances our understanding of the nascent credit rating industry in China. Dhawan and Yu (2015) and Livingston et al. (2017) find that Chinese bond ratings are informative towards corporate bond yield. Korkeamäki et al. (2014) reach a similar conclusion in the syndicated loans market. Poon et al. (2013) show the role of credit rating in reducing the underpricing of seasonal offerings. While these studies mainly focus on the informational role of the incumbent issuer-pay CRAs in China, there is limited evidence on the CRAs' reactions to the entry of a new credit rating agency, CCR. To our best knowledge, we are the first to provide such evidence. Our findings improve our understanding of the implication of the entry of CCR (a new combined investor-pay and public utility model) by documenting its effect on the information asymmetry and the rating quality of the incumbent CRAs.

3.2 Sample and Methodology

3.2.1 Data

I collected data from Wind, ChinaBond and CCR.

I manually constructed the sample by merging two rating databases from CCR and all other issuer-pay CRAs. CCR's rating database consists of issuer credit ratings between 2012 and the end of 2015. Each observation is an issuer credit rating corresponding to a certain rating action including a new rating assignment, affirmation, upgrade and downgrade. Throughout the thesis, I use the rating action of 'new rating assignment' from CCR to identify the date when CCR initiated coverage of each firm. I deleted firms that only obtained an initial rating but that have not been followed by CCR since, leaving 2,440 observations for corporate ratings representing 870 firms in CCR's original database. I obtained credit ratings for nine other issuer-pay CRAs between 2006 and the end of 2015 from Wind Info, leaving 26,069 firm–year–CRA observations for 3,663 firms. The data sample excludes ratings for financial institutions, treasury bonds and enterprise set bonds and other non-rated or small volume bond categories. Therefore, I have two unbalanced cross-sectional data. I merged these two datasets by manually matching the company names and yearly information. I successfully merged 869 out of 870 firms from CCR's rating dataset.

For each firm, I identified the day when CCR initiated coverage of the firm as the first coverage date. I then defined the period after the first coverage date as the *post-coverage* period and the period before the first coverage date as the *pre-coverage* period.

After this, I merged the rating sample with the Wind Info to obtain firms' financial information. The final sample contains 11,520 firm–year–CRA observations, representing 869 firms that incumbent issuer-pay CRAs originally rated and CCR later initiated coverage of between 2006 and 2015.

3.2.2 Sample Description

Panel A of Table 3.1 compares the descriptive statistics for firms rated by incumbent issuer-pay CRAs that are later covered by CCR with firms not covered by CCR between 2006 and 2015. On average, firms rated by both types of CRAs are larger, as measured by sales. This implies that CCR does not randomly choose firms to cover. For example, the mean sales (log) of firms covered by CCR is 5.048, while the mean sales of firms not covered by CCR is only 3.211. This difference is significantly different from zero at a 1% confidence level. Firms rated by both types of CRAs have a relatively larger size, higher leverage, ROA and tangibility and lower growth rate.

Table 3.1: Rating Sample Summary Statistics

Table 3.1 compares the statistics of firms rated by both CCR and issuer-pay CRAs to firms only rated by issuer-pay CRAs between 2006 and 2015. *Rating* is a numerical value based on a notch basis as follows: AAA, AAA– = 5; AA+, AA = 4; AA– = 3; A+ = 2; others = 1; *sales* is the natural logarithm of sale; *leverage* is the ratio of total liability from the balance sheet to total assets; *ROA* is the return on assets that represents the profitability; *tangibility* is the ratio of property, plant and equipment to total assets; *growth* is the year-to-year increase of operating income; *cash equivalent* is the ratio of cash, tradable asset and receivable over current asset; all above variables are measured at the time t – 1. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels respectively.

Summary statistics of the controlled group and treatment group								
		Rating	Sales	Leverage	ROA	Tangibility	Growth	Cash equivalent
Firms not covered by CCR	Mean	3.898	3.211	53.829	0.449	0.180	0.853	0.567
	Std.dev	0.008	1.599	17.108	0.456	0.182	16.170	1.681
	Min.	1	–4.605	0.080	-6.578	0.000	–0.999	0.000
	Max.	6	8.437	162.200	6.300	0.961	1029	100.018
	N	14,549	14,485	14,501	14,480	14,432	14,437	14,485
Firms covered by CCR	Mean	4.769	5.048	63.023	0.577	0.295	0.233	0.419
	Std.dev	0.010	1.645	13.933	1.456	0.208	0.671	0.402
	Min.	1	–2.303	6.840	–4.072	0.000	–0.987	0.000
	Max.	6	10.268	139.85	86.112	0.969	23.680	13.884
	N	11,520	11,505	11,501	11,504	11,499	11,489	11,499
Mean difference		0.871***	1.837***	9.194***	0.128***	0.115***	–0.620***	–0.148***
Median difference		1***	1.843***	9.530***	0.125***	0.134***	0.018***	–0.027***

3.3 Methodology and Baseline Empirical Results

In this section, I present the methodology and baseline empirical results that show the effects of CCR rating initiation on the informativeness of incumbent issuer-pay CRAs' rating changes. According to Xia (2013), information content of credit rating changes of issuer-pay CRAs is used to measure the rating quality improvement. The specific method I employ is to analyse the bond return reactions to rating change announcements of issuer-pay CRAs before and after CCR's coverage initiation by setting up an event study in which the price changes for CPs, MTNs, CBs and EBs in China are considered. This approach has been widely used by previous studies (Ederington & Goh 1998; Hand, Holthausen & Leftwich 1992; Holthausen & Leftwich 1986; Hull, Predescu & White 2004; Jorion, Liu & Shi 2005; Katz 1974; Weinstein 1977). This study combines an event study with CCR's coverage initiation to estimate the influence of CCR's coverage.

A greater market reaction indicates that rating changes of issuer-pay CRAs have more information and suggests the ratings' higher information quality. If incumbent issuer-pay CRAs become more informative after CCR's rating initiation, the bond market has a greater reaction to the rating change announcements.

3.3.1 Event Study Set-Up

I collected the information of 12,784 relevant bonds issued in China between 2006 and 2015. The rating change is defined as any rating differences made by the issuer-pay CRAs compared to the prior rating assigned by any issuer-pay CRA for each issuer. By following the announcements of issuer-pay CRAs, I obtained 1,820 rating changes on these bonds' issuers. Among them, there are 1,395 upgrades and 425 downgrades. The event date is the day in which the rating change is announced; thus, I have multiple event dates, one for each rating change of every issuer. Subsequently, I merged the firms who received rating changes with bonds issued by this firm. Thus, the rating change for one firm might have an influence on several bonds' prices. I calculated the cumulative abnormal return (CAR) for each bond. To be sure, the consideration of possible co-movements of stock and bond markets is nothing new in the literature, dating back to Pinches and Singleton (1978) that analyze the adjustment of stock prices to bond rating changes.

Following the study of Ferri et al (2013), I used the CARs (expressed in percentage) over the 21-trading-day event window (from t – 10 to t + 10) to measure the magnitude of market reactions to rating changes; t is the event date. As the bond market is less liquid than stock market, I choose 21 days as the event window. In robustness check, I altered the event window to 11 days, the results are still hold. The estimation window is 90 trading days (from t – 120 to t – 30). Daily abnormal returns (AR) are calculated based on the market model (Fama & French 1993). Specifically, I ran the following OLS model for each bond:

$$R_{i,t} = \alpha_i + \beta_i R_{M,t} + \varepsilon_i \tag{3.1}$$

where $R_{i,t}$ and $R_{M,t}$ define a bond's daily returns and daily return of a market portfolio over a 90-trading-day period ending 30 trading days before the event day. The daily return of a market portfolio is defined as the daily change of the China Bond Index (CBA).[22] For each period, individual bond returns and market return are calculated as follows:

$$R_{i,t} = \ln(\frac{P_{i,t}}{P_{i,t-1}}) \tag{3.2}$$

$$R_{M,t} = \ln(\frac{CBI_{i,t}}{CBI_{i,t-1}}) \tag{3.3}$$

Next, for each bond, I use the estimated α_i and β_i, namely $\hat{\alpha}_i$ and $\hat{\beta}_i$, to calculate the daily expected returns (the normal returns) during the 21-day event window, from $\hat{R}_{i,t-10}$ to $\hat{R}_{i,t+10}$, as

$$\hat{R}_{i,t`} = \hat{\alpha}_i + \hat{\beta}_i R_{M,t`} \text{, where t` } \in [-10, 10] \tag{3.4}$$

Then, I calculate the daily AR, which is defined as the difference between the actual return and the estimated return in each of the 21 days:

$$AR_{i,t`} = R_{i,t`} - \hat{R}_{i,t`} \text{, where t` } \in [-10, 10] \tag{3.5}$$

The CAR is the sum of the daily AR during the 21 days:[23]

$$CAR_{i,t`} = CAR_{i,t`-1} + AR_{i,t`} \text{, where t` } \in [-10, 10] \tag{3.6}$$

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[22] Since 5 February 2006, China Bond Index has been developed and issued every trading day by China Central Depository & Clearing Co., LTD.

[23] I also employed another way to calculate CAR as the total AR during the 21-trading-day event window as a robustness check; the results still hold.

After merging with CCR's coverage database and the available market trading database, finally I obtained 832 upgrades and 264 downgrades for 766 bonds issued by 361 firms who are covered by both CCR and incumbent issuer-pay CRAs.

3.3.2 Baseline Empirical Results

Table 3.2 presents the multivariate results from the regression by applying the following model:

$$CAR_i = \alpha + \beta_1 CCRfirstcover_i + \beta_2 X_i + \partial_i + \varepsilon_i \tag{3.7}$$

where X_i and ∂_i represent the control variables (leverage, tangibility, sales, growth and ROA) and industry dummy respectively. $CCRfirstcover_i$ is a dummy variable equal to one if the event date is in the post-coverage period, otherwise zero. The results for downgrade and upgrade samples show that the market reaction is significantly negative towards downgrade announcements and not significantly responsive to upgrades. Specifically, in Column 1, switching from the pre-coverage to post-coverage period increases the magnitude of the 21-day CAR decreases by over 2.735% for downgrades, which is economically sizeable for the bond market. When considering the control variables and industry fixed effect in Columns 2 and 3 respectively, the same conclusion was obtained. These results are consistent with the literature that suggests that the market has a greater reaction to rating downgrades than upgrades (Dichev & Piotroski 2001; Ederington & Goh 1998; Galil & Soffer 2011). A reason for these asymmetric reactions to upgrades and downgrades is that firms usually voluntarily release good news to the market well before rating changes, thus reducing the market reaction (Ederington & Goh 1998). Another possible reason is the regulatory use of credit ratings (Ferri, Lacitignola & Lee 2013) that make investors care more about downgrades as an investment restriction on ratings.

This unbalanced results between downgrades and upgrades also point to a reputational mechanism. As failure to reveal negative information has a higher reputation cost than failure to reveal positive information for CRAs (Ellul, Jotikasthira & Lundblad 2011; Kisgen 2007), incumbent issuer-pay CRAs are likely to pay more attention on downgrades (which reveal negative news) in the face of CCR's lower and more informative ratings to avoid the higher reputation cost (Bar-Isaac & Shapiro 2013; Bolton, Freixas & Shapiro 2012). This improves the information content of issuer-pay CRAs' rating downgrades. I will further discuss the reputation concerns for different issuer-pay CRAs in Section 3.5.1. For other analyses, the focus will be on the effects of downgrade announcements.

3.4 Endogeneity Tests

One potential problem of the analyses thus far is that CCR's coverage initiation is not exogenously determined. Although CCR states that its coverage is random, I still observe significant differences of financial characteristics between covered and uncovered firms. Therefore, CCR's coverage may come from the requests of their clients or from the government regarding the quality of the existing rating. If this concern independently stimulates incumbent issuer-pay CRAs to adjust their ratings regardless of CCR's actions, the effect of CCR's entry and the reputational mechanism will be overestimated. In Section 3.4, I used two approaches to remedy this issue: an IV analysis and PSM. From here on, I will focus on the market reaction to downgrades.

Table 3.2: Information Content of Rating Changes of Issuer-Pay Rating Agencies

Table 3.2 presents the 21-trading-day CARs (in percentage) for bonds surrounding the rating change announcements of incumbent issuer-pay CRAs. The sample consists of issuer-pay CRAs' rating change announcements for 361 firms that CCR initiated coverage of between 2012 and the end of 2015. Rating changes are between 2006 and 2015. There is a total of 832 upgrades and 264 downgrades for 766 bonds. *CCRfirstcover* is a dummy variable equal to one if the event date of rating change is during the post-coverage date, otherwise zero. The left-hand-side variable is the 21-day CARs surrounding rating change announcements. *Sales* is the natural logarithm of sales; *leverage* is the ratio of total liability from the balance sheet to total assets; *ROA* is the return on assets that represents the profitability; *tangibility* is the ratio of property, plant and equipment to total assets; *growth* is the year-to-year increase of operating income; *cash equivalent* is the ratio of cash, tradable asset and receivable over current asset; all above variables are measured at the time t-1. Industry fixed effects are indicator variables for firms' industry. Standard errors are in parentheses. R-squared is reported. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels respectively.

	Downgrades			Upgrades		
	(1)	(2)	(3)	(1)	(2)	(3)
CCRfirstcover	–2.735**	–2.737**	–3.862***	–0.071	–0.120	–0.154
	(1.306)	(1.348)	(1.455)	(0.136)	(0.140)	(0.144)
Sales		–0.701	–0.247		0.111*	0.114*
		(0.624)	(0.709)		(0.061)	(0.067)
Leverage		0.229***	0.256***		–0.010	–0.009
		(0.078)	(0.080)		(0.008)	(0.008)
ROA		0.153	0.147		–0.024	–0.027
		(0.204)	(0.209)		(0.020)	(0.020)
Tangibility		–3.681	–6.153		0.151	–0.015

		(3.255)	(3.760)		(0.358)	(0.419)
Growth		0.466	0.079		-0.022	0.024
		(0.900)	(0.915)		(0.082)	(0.082)
Cash equivalent		7.269***	8.612***		0.062	0.029
		(2.315)	(2.383)		(0.227)	(0.230)
Constant	0.254	–13.953**	–14.316**	–0.127	0.059	0.092
	(1.030)	(5.407)	(5.796)	(0.091)	(0.540)	(0.579)
Observations	264	262	262	832	831	831
R-squared (Adjusted)	0.017	0.083	0.150	0.000	0.006	0.032
Industry fixed effects	No	No	Yes	No	No	Yes

3.4.1 Instrumental Variables Analysis

I employed an IV analysis to establish the casual role of CCR's coverage initiation on issuer-pay CRAs' rating adjustment. From the discussion on descriptive statistics in Section 3.2, I find that CCR's coverage follows the rule of 'a large firm'. Based on this law, I used the previous year's average asset of each issuer's industry as an instrument for the timing of CCR's coverage for the firm. Industry categories are classified by codes defined by CSRC and widely used in China. For each year, I calculated the issuer's industry average total asset based on the financial data in prior years using firms who were not covered by CCR as of 2015. I also used covered firms' data to construct the instrument as a robustness check, obtaining similar results (see Section 3.6.4). The idea here is that if the issuer's industry has an overall large total asset, then the relevant issuer is also likely to be a larger firm and thus more likely to be covered by CCR. The IVs should not be related to the quality or informativeness of issuer-pay CRAs' ratings for that particular firm, which means the industry average total asset should be independent to rating information content. I confirm this hypothesis in this section.

Based on the methods used by Cohen, Frazzini and Malloy (2012) and Xia (2013), I employed a logit model in the first-stage regression to regress CCR's coverage initiation (i.e., *CCRfirstcover* dummy) on the industry average total asset (i.e., *Ind–Mean–Asset*) and other same control variables in the second-stage regression under a bond-fixed-effect setting. From the first-stage regression, I obtained the predicted probability that CCR would initiate coverage in any given year for a given firm. Then, for each firm, I designated the first day of the year with the highest predicted probability as the instrumented date for CCR's coverage initiation (i.e., the *instrumented coverage date*). Then, I defined the *instrumented CCRfirstcover* dummy as equal to one for observations whose rating change announcements happened after the instrumented coverage date (otherwise zero). This *instrumented CCRfirstcover* is used in the second-stage regression. The regression results are presented in Table 3.3.

Column 1 of Table 3.3 presents the result of first-stage regression, from which the instrument is significantly positively related to the time of CCR's coverage initiation. Therefore, this result is consistent with the assumption that CCR is more likely to rate large firms. The LR chi-squared statistics is significant at a 1% confidence level, which indicates that the *Ind–Mean–Asset* is not a weak instrument. Column 2 presents the results of second-stage regression under different models, and the previous findings in Table 3.2 are preserved. Specifically, the market reaction to the downgrades of issuer-pay CRAs (shown by the change of CARs) is more stronger and significantly different from zero in the post-coverage period than the pre-coverage period (i.e., –3.156% and significant at 5%). Therefore, this confirms the casual effect of CCR's coverage on ratings informativeness of incumbent CRAs.

Further, we need to confirm that the instrument we chose (*Ind–Mean–Asset*) does not directly affect the rating quality of incumbent issuer-pay CRAs for each given issuer. To ensure this, I examined the significance of the correlation between the instrument (i.e., *Ind–Mean–Asset*) and incumbent CRAs' rating information content in the sample of non-CCR-covered firms. This sample can mute the indirect channel of CCR's coverage, thus allowing us to purely focus on the direct channel. If the instrument is independent from the rating informativeness, we should not observe a significant correlation between them. Similarly, I used information content of issuer-pay CRAs' rating changes to measure the rating quality. First, we tested the significance of Pearson correlation between them. There is only a correlation of 0.006, with a P value of 0.845, which indicates that the correlation is very small and not statistically significant. This result shows that the instrument is not likely to be directly related to rating quality of issuer-pay CRAs. Second, we utilised a multivariate model, shown in Eq. 3.8, to further test the correlation between the above two variables.

$$CAR_i = \alpha + \beta_1 Ind\ Mean\ Asset_i + \beta_2 X_i + \partial_i + \varepsilon_i \qquad (3.8)$$

Based on the prediction above, the multivariate regression should show a statistically significant result for β_1 if the instrument directly causes the rating quality change of issuer-pay CRAs. The regression result is presented in Column 3 of Table 3.3, and I applied the same control variables to that in Column 2 for the second-stage regression. In line with the univariate correlation test, we do not observe a significant relationship between the industry average total asset and CARs, the measurement of rating quality of issuer-pay CRAs.

Through the IV approach, we confirm the role of CCR's coverage initiation on rating informativeness of incumbent issuer-pay CRAs, assuming the coverage initiation is casual. The instrument I employed is not likely to be correlated with the dependent variable.

Table 3.3: Instrumental Variable Regression for Downgrades

Table 3.3 presents the results of the IV regressions. The first stage is logit regression of the *CCRfirstcover* dummy on *Ind–Mean–Asset*. *CCRfirstcover* is a dummy variable equal to one if the event date of rating change is during the post-coverage date, zero otherwise. *Ind–Mean–Asset* is the industry average total asset (measured as the logarithm of total asset) of each firm's industry in the prior year, calculated using only issuer-pay CRA-rated firms not covered by CCR as of 2015. Also included in the first stage are the same control variables as those in the corresponding second stage and for the exclusion restriction test. Industries are classified by codes defined by CSRC. The first day of the issuer-year with the highest predicted probability of CCR's coverage initiation for each issuer is assigned as the instrumented date for CCR's coverage initiation. The instrumented CCRfirstcover equals one if the event date of rating changes is after the instrumented date for CCR's coverage initiation, zero otherwise. In the second-stage regression in Column 2 and the exclusion restriction test in Column 3, the left-hand-side variable is the 21-day CARs (in percentage change) surrounding rating change announcements. Standard errors are in parentheses. R-squared is reported. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels respectively.

	First stage	Second stage	Exclusion restriction
	(1)	(2)	(3)
CCRfirstcover (instrumented)		–3.156**	
		(1.358)	
Ind–Mean–Asset	7.537***		–2.069
	(1.230)		(1.707)
Sales	0.354*	–0.620	0.385
	(0.204)	(0.701)	(0.244)
Leverage	0.023	0.270***	–0.027
	(0.022)	(0.080)	(0.024)
ROA	–0.015	0.204	–0.094
	(0.056)	(0.208)	(0.052)
Tangibility	1.720	–7.676**	–2.815**
	(1.049)	(3.790)	(0.969)
Growth	–0.543	0.494	0.057
	(0.544)	(0.901)	(0.073)
Cash equivalent	1.001	8.631***	–0.005
	(0.667)	(2.393)	(0.257)
Constant	–43.126***	–14.854**	13.378
	(7.157)	(5.800)	(9.897)
Observations	257	262	385
LR Chi-squared	122.29		
Prob (Chi-squared)	0.000		
(Pseudo) R-squared	0.359	0.144	0.043
Industry fixed effects	Yes	Yes	Yes

3.4.2 Propensity Score Matching Method

The second method applied to remedy the endogeneity problem is the PSM approach. I matched CCR-rated firms in the sample (treated group) to those not rated by CCR (control group) from 2012 to 2015, based on various dimensions that are likely to predict CCR's coverage decision. The idea is that by putting together firms (firm–year–CRA) that are similar in these dimensions, we would obtain matched firm–year–CRA that designated when CCR would have begun to rate the firm had it decided to cover the firm. I used the first day of the matched year as the hypothetical date of CCR's coverage initiation and examined whether the information content of incumbent issuer-pay CRAs improved in the matched sample after the hypothetical CCR's coverage initiation.

I matched the sample firms based on a set of pre-treated (i.e., one year prior to CCR coverage) characteristics, and I used 1-to-1, 1-to-3 and 1-to-5 nearest-neighbour matching methods respectively. Column 1 of Table 3.4 simply repeats Column 3 of Table 3.2 for downgrades for comparison purposes. PSM regressions on the hypothetical CCR's coverage initiation are shown in Columns 2 to 4, from which I cannot observe any statistically significant relationship between CCR's coverage and market reaction.[24] The results indicate that previous findings on the influence of CCR's coverage are unique for issuers who are actually covered by CCR (treatment group), while for the matched sample the information content of issuer-pay CRAs is not significantly related to CCR's actions. This further shows that CCR's coverage reveals more information on the bond market, which enriches the rating informativeness of incumbent issuer-pay CRAs and, in turn, causes a greater market reaction. This reinforces the argument that CCR's entry improves the information quality of ratings in the bond market in China.

[24] For the subgroup regression in Section 3.4, we also applied the PSM method. Consistent with the result in Table 3.4, we did not obtain significant results to show the relationship between hypothetical CCR's coverage and ratings quality.

Table 3.4: Propensity Score Matching for Downgrades

Table 3.4 presents the results of the nearest-neighbour PSM where each CCR-covered issuer is matched with one, two or three firm(s) that are not rated by CCR as of the end of 2015 respectively. The CCR-covered sample consists of issuer-pay CRAs' rating downgrade announcements that CCR initiated coverage of between 2012 and the end of 2015. Rating changes are between 2006 and 2015. Firms are matched based on their pre-treated (one year prior to CCR's coverage) firm characteristics. The characteristics include size, leverage, profitability, tangibility sales and growth rate. The first day of issuer-year from the non-CCR-covered (control) group that is matched with the CCR-covered (treated) firm is applied as the hypothetical coverage initiation time for the firm. Hypothetical CCRfirstcover equals one if the downgrade is after the hypothetical coverage time, zero otherwise. Standard errors are in parentheses. R-squared is reported. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels respectively.

	(1)	(2) 1-to-1	(3) 1-to-3	(4) 1-to-5
(Hypothetical) CCRfirstcover	–3.862***	–0.057	–1.102	–0.927
	(1.455)	(0.650)	(0.841)	(0.780)
Sales	–0.247	0.432*	0.641	0.572
	(0.709)	(0.256)	(0.394)	(0.347)
Leverage	0.256***	–0.059**	–0.072**	–0.060**
	(0.080)	(0.026)	(0.034)	(0.029)
ROA	0.147	–0.052	–0.131**	–0.107*
	(0.209)	(0.059)	(0.065)	(0.061)
Tangibility	–6.153	–4.596***	–6.700**	–4.986**
	(3.760)	(1.614)	(2.606)	(2.196)
Growth	0.079	1.016	-0.005	0.071
	(0.915)	(0.731)	(0.283)	(0.269)
Cash equivalent	8.612***	–0.325	–0.680	–0.827
	(2.383)	(1.557)	(1.971)	(1.565)
Constant	–14.316**	3.412	6.103**	4.765*
	(5.796)	(2.305)	(2.963)	(2.540)
R-squared	262	82	177	206
Observations	0.150	0.247	0.090	0.077
Industry fixed effects	Yes	Yes	Yes	Yes

3.5 Analyses Conditional on Reputational Differences and Investor Protection Environment

Two mechanisms through which CCR's coverage initiation can improve information content and thus the rating quality of incumbent issuer-pay CRAs are investigated in this section.

3.5.1 The Effect of China Credit Rating's Coverage Initiation Conditional on Reputational Differences among Issuer-Pay Credit Rating Agencies

Similar to Section 2.4, I propose that an important mechanism through which CCR's coverage improves ratings informativeness of issuer-pay CRAs in China is the reputation of issuer-pay CRAs. In other words, reputable incumbent CRAs are more likely to adjust their rating strategies following CCR's coverage initiation, improving the quality of their ratings, because they fear losing their reputation. This proposal is consistent with the reputational mechanism mentioned in Section 2.4 (Bar-Isaac & Shapiro 2013; Bolton, Freixas & Shapiro 2012; Mathis, McAndrews & Rochet 2009; Opp, Opp & Harris 2013; Skreta & Veldkamp 2009). Moreover, the asymmetric results between downgrades and upgrades imply that reputation concerns may be a mechanism.

Therefore, I expect that incumbent CRAs with a better reputation will experience a greater improvement in rating quality; thus, their rating changes are associated with more market reactions following CCR's coverage initiation.

As previously discussed, only CCXI and Lianhe are recognised as reputable issuer-pay CRAs in China. The other issuer-pay CRAs belong to the non-reputable group. The study estimated the model in Table 3.2 and tested whether the coefficient of *CCRfirstcover* differed between the reputable and non-reputable groups. Column 1 of Table 3.5 presents the results from this analysis. The coefficient on *CCRfirstcover* is more negative in the subsample of reputable issuer-pay CRAs and the difference in coefficients is statistically significant.

This finding is consistent with the expectations and suggests that investors react more to rating changes issued by reputable issuer-pay CRAs during the post-coverage period, thus indicating a greater improvement of rating information content (quality) of reputable issuer-pay CRAs following CCR's coverage. This also confirms the existence of the reputational mechanism, through which CCR's coverage influences the enhancement of rating quality. However, these results are contrary to the criticism that issuer-pay CRAs in China do not care about their reputation when assigning ratings (Bottelier 2003; Kennedy 2008; Xu & Han 2013).

3.5.2 The Effect of China Credit Rating's Coverage Initiation Conditional on Issuers' Investor Protection Environment

In this section, I use the IPI and rating frequency to measure the investor protection environment of an issuer, similar to Section 2.4.2.

Columns 2 and 3 of Table 3.5 summarise the results of the analysis conditional on issuers' investor protection environment. Consistent with expectations, the coefficient of *CCRfirstcover* is more negative for firms with better investor protection environment (i.e., issuers have higher rating frequency or come from provinces with a higher IPI). These findings suggest that, disciplined by the coverage of CCR, incumbent issuer-pay CRAs are more likely to adjust their rating strategy when rating issuers who have a better investor protection environment.

Table 3.5: Information Content of Rating Changes of Issuer-Pay Rating Agencies for Downgrades—Classified by Reputation of Issuer-Pay CRAs

Table 3.5 presents the 21-trading-day CARs (in percentage) for bonds surrounding the downgrades rating change announcements of incumbent issuer-pay CRAs, classified by their reputation. The reputable group consists of two CRAs: CCXI and Lianhe. The non-reputable group consists of the other seven issuer-pay CRAs. The Diff. of. Coefficient equals the coefficient of CCRcover*Post for reputable group minus that for non-reputable group for column 1; the coefficient of CCRcover*Post for high-IPI group minus that for low-IPI group for column 2; the coefficient of CCRcover*Post for high-frequency group minus that for low-frequency group for column 3, respectively. Standard errors are in parentheses. R-squared is reported. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels respectively.

	(1)		(2)		(3)	
	Non-reputable	Reputable	Low IPI	High IPI	Low frequency	High frequency
CCRfirstcover	–0.431**	–5.912**	–0.167	–6.011***	0.085	–4.206**
	(0.214)	(2.308)	(0.232)	(2.225)	(0.252)	(1.983)
Diff. of coefficient	–5.481**	chi2 = 5.59	–5.844***	chi2 = 6.82	–4.291**	chi2 = 4.61
Sales	0.121	–0.465	0.031	–1.035	-0.050	0.006
	(0.116)	(0.839)	(0.116)	(1.052)	(0.179)	(1.048)
Leverage	–0.032**	0.574***	0.016	0.642***	–0.014	0.593***
	(0.014)	(0.202)	(0.011)	(0.206)	(0.014)	(0.187)
ROA	–0.040*	0.223	0.062	0.847**	–0.027	–0.019
	(0.024)	(0.268)	(0.049)	(0.349)	(0.031)	(0.348)
Tangibility	0.016	–9.607**	–1.046	–21.866**	–1.118	–2.291
	(0.477)	(4.541)	(0.734)	(8.681)	(0.852)	(3.958)
Growth	0.708***	0.212	–0.010	–0.497	0.655***	0.769
	(0.182)	(0.636)	(0.447)	(0.695)	(0.140)	(0.680)
Cash equivalent	–0.307	15.922**	0.740*	12.185***	–0.230	30.038***
	(0.511)	(7.877)	(0.385)	(4.480)	(0.307)	(10.265)
Constant	1.894**	–36.588**	–1.437**	–33.076***	1.375	–45.689***
	(0.941)	(14.779)	(0.707)	(11.266)	(0.901)	(14.350)
Observations	135	127	132	130	114	148
R-squared	0.135	0.273	0.128	0.331	0.117	0.349
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

3.6 Robustness Test

3.6.1 Alternative Sample Period

This study also considers that there may be a time delay in the influence of CCR's entry. Therefore, I deleted the observations in 2012 and assumed that the market needed one year to react to CCR's coverage. The result does not change qualitatively (see Appendix 3.1).

3.6.2 Alternative Event Window and Alternative Estimation Window to Calculate Cumulative Abnormal Returns

I changed the event window from 21 days to 11 days, a shorter reaction cycle, to calculate the cumulative AR during the 11-trading-day event window for bonds surrounding downgrades rating change announcements. The results still hold (see Appendix 3.2). Moreover, I changed the estimation window from 90 trading days (t – 120, t – 30) to 60 trading days (t – 80, t – 20) to include more valid data. The results still hold (see Appendix 3.2).

3.6.3 An Alternative Way to Calculate Instrumental Variables

As discussed in Section 3.4.1, I applied another method to calculate the IV (i.e., industry average total asset) based on the financial data in the prior year using firms who were covered by CCR as of 2015. All results are unchanged qualitatively (see Appendix 3.3).

3.6.4 Additional Proxy to Measure the Investor Protection Environment

I used the MI in 2009 (Fan, Wang & Zhu 2011) as a proxy for the information environment. The high MI group consists of firms from provinces with a higher MI than the median level; the low MI group consists of firms from provinces with a lower MI than the median level. The empirical result does not change qualitatively (see Appendix 3.4).

3.6.5 Event Study Using a Different Rating Classification to Define Rating Changes

As another robustness check, I rematched the events of rating change using a wider rating scale. I reclassified the ratings to nine scales as follows: AAA, AAA– = 9; AA+ = 8; AA = 7; AA– = 6; A+ = 5; A = 4; A – = 3; BBB+ = 2, others = 1. The previous results still hold (see Appendix 3.5).

3.7 Conclusion

This chapter examined how the entry of CCR affected the information quality of ratings issued by incumbent issuer-pay CRAs in China. By comparing the information content of incumbent issuer-pay CRAs before and after CCR's coverage initiation, this research found there was a significant improvement in the rating quality of incumbent CRAs. Their ratings incorporated more information content and triggered a greater market reaction to their rating downgrade announcements following CCR's coverage.

The IV approach and PSM method were employed to remedy the possible endogeneity issue, establishing the causal role of CCR's coverage initiation. This study further found that all ratings of incumbent CRAs were lower than CCR's, and only the downgrades caused greater reactions during the post-coverage period. This asymmetric finding suggests that the rating strategy adjustment of incumbent CRAs are responsive to the reputational mechanism elevated by CCR's entry.

This research also found that CCR's entry had a greater effect on more reputable issuer-pay CRAs, and a greater influence on issuers with a better investor protection environment. This finding indicates that incumbent CRAs' rating behaviour can be disciplined by CCR's entry through their own reputation concerns and outside supervisors.

The findings in this chapter supplement the existing literature that discusses how to improve the rating quality of issuer-pay CRAs. It also complements the debates on the reputational mechanism of CRAs. Further, it calls for more attention on the importance of issuer-pay CRAs' reputations and the construction of a better investor protection environment.

Chapter 4
Certification through Reputation of a Credit Rating Agency

This chapter investigates whether certification via reputable CRAs is beneficial to issuers in the bond market in China. After considering the issuer-reputable CRA match, I find that bonds rated by the most reputable CRAs are associated with a lower yield spread (higher bond price), revealing investors' recognition of the rating quality of reputable CRAs. This result is consistent with the traditional certification hypothesis and underlying reputational mechanism. I further find that the investor protection environment and issuer's risk are two mechanisms through which the certification effect works. I also find this certification effect was reinforced after the entry of CCR. Section 4.1 provides a brief introduction and Section 4.2 analyses the related literature. Section 4.3 focuses on sample and methodology, while 4.4 presents the baseline empirical results. Section 4.5 estimates the effect of CCR's entry on the certification role of reputable CRAs. Section 4.6 is a robustness test. Section 4.7 concludes the chapter.

4.1 Introduction

In this chapter, I test the certification hypothesis from the issuer's point of view by asking whether certification benefits issuers through reducing financing cost in the bond market.

In the bond market, CRAs play the important role of connecting bond issuers with bond investors. The most important reason why CRAs are valuable is because they can reduce the informational cost of capital for issuers. This role arises from the typical information asymmetry between issuers and investors during bond issuance. Ackerloff (1970) claimed that such an information gap would deteriorate investors' trust of issuers, or even destroy the whole market. However, CRAs, as an intermediary between insiders and outsiders, are in a perfect position to reduce information asymmetry and lower the cost of capital for bond issuers.

Previous research has estimated the important role of CRAs in reducing information asymmetry between bond issuers and bond investors, and subsequently reducing the cost of debt. For instance, Livingston and Zhou (2009) found that bonds with split ratings had a higher yield because investors required more compensation for the greater asymmetric information behind the rating difference. In addition, Tang (2009) analysed debt costs after Moody's change on its rating granularity and found that firms with more refined ratings had lower debt costs than those with less refined ratings. Sufi (2009) highlighted the certification effect of bank loan ratings on the financing and investment activities of issuers, as rating solicitation can also reduce information asymmetry. The author further advocated that due to the greater reputation of Moody's and S&P, firms with bank loan ratings from them could get access to debt financing more easily.

Conversely, how does an issuer-pay CRA solve its own information problem vis-a-vis the investors, particularly as it collects most of its revenue from issuers? One solution is the 'reputation capital' at stake for CRAs. CRAs are repeat player in the markets; thus, their long-run business is closely related to their reputation. If they only focus on short-term revenue by initiating favourable ratings, investors will lose confidence in them in the long run, causing reputation and income loss. As long as the present value of future income is greater than the short-term profit from fraud, CRAs will choose not to defraud investors.

Therefore, reputation is a valuable asset in the credit rating industry. The intention to protect reputation capital will affect CRAs' rating imitation decisions. As bad bond performance (e.g., default in the future) will damage the reputation of rating agencies, relatively reputable CRAs will rate high-quality issuers that pose little risk to their reputation. In turn, aware of the reputation concerns of CRAs, investors take reputable CRAs' ratings as positive signals, and, ceteris paribus, the issuer will have a lower debt cost. This is associated with the certification hypothesis that underwriters can help to reduce information asymmetry between insiders and outsiders by certifying issuer quality through their reputation (Booth & Smith 1986).

Although the role of CRAs' reputations has been discussed theoretically, the empirical evidence is addressed less often, particularly in the emerging market. In this chapeter, issuance data between 2006 and 2015 is used to empirically estimate the benefit of certification from reputable CRAs to issuers in the bond market in China. After controlling the issuer-CRA selection bias, I found that reputable CRAs obtained lower bond yields for their clients. In addition, the investor protection environment and issuer's risk are two mechanisms through which the certification effect has influence.

Moreover, according to the results from Chapters 2 and 3, reputable CRAs in China experienced a greater improvement in rating quality after the entry of CCR. Therefore, I have an opportunity to further analyse whether CCR's entry affected the certification role of existing reputable issuer-pay CRAs. I find that bonds rated by reputable CRAs obtained lower bond yields after CCR's entry, and the certification effect to reduce debt cost by reputable CRAs was stronger for CCR-uncovered issuers than covered issuers.

Overall, the findings suggest that CRAs' rating decisions reflect reputation concerns and are thus informative of issue quality. Investors take reputable CRAs' ratings as a positive signal and assign a lower yield for issuers. This effect is reinforced by the entry of an independent CRA, verifying the reputational mechanism from another perspective.

4.2 Related Literature

After the subprime crisis and sovereign debt crisis in Europe, the failure of CRAs has been widely discussed by the public and academia. The discussion was directed at their capital: their reputation. There are several branches of studies on the reputation of CRAs and financial intermediaries in general. Nevertheless, this thesis will focus on the relationship between intermediary reputation and security price.

4.2.1 Theory

Theoretically, there are still inconsistencies between the certification hypothesis and market power hypothesis in relation to the role of a financial intermediary's reputation.

In the bond market, the certification hypothesis is at first applied on underwriters. It suggests that with their reputation at stake, reputable underwriters can verify the quality of their issuers, thus reducing information asymmetry (Allen 1990; Booth & Smith 1986; Titman & Trueman 1986). The certification via reputable underwriters can lower issuers' information cost, thus lowering bond issuance yield. This certification effect works because reputable underwriters apply stricter evaluation standards to avoid reputation cost (Chemmanur & Fulghieri 1994). There are still opposing arguments regarding the certification hypothesis caused by moral hazard and competition. As long as underwriters build up a strong reputation, they have the market power and incentive to milk their reputation (Chemmanur & Fulghieri 1994). Thus, it is highly possible that reputable underwriters are associated with incorrect evaluation.

In terms of the certification effect via reputation of the CRAs, some commentators believe that the reputational mechanism can alleviate any conflict of interest to some extent. When issuer-pay CRAs consider the long-term reputation cost, they tend to provide more informative ratings to avoid investors' or regulators' derecognition of their rating inflation (Bar-Isaac & Shapiro 2013; Bolton, Freixas & Shapiro 2012). Further, Goel and Thakor (2010) found that CRAs' concern over their reputation can induce them to invest more, and that reputation tends to dominate any conflicts of interest in the industry (Covitz & Harrison 2003). Fischer's (2015) model uses a dynamic setting to capture the effects of CRAs' reputations, and the author found that low-quality bond issuers generally tend to match low-quality CRAs. However, the same debate between certification and market power also exists in the credit rating industry. For example, model built by Mathis, McAndrews and Rochet (2009) suggested that agencies increase their ratings using their cumulative reputation. The truth-telling incentives are weaker when CRAs have more business from rating complex products.

4.2.2 Hypothesis development

Base on the discussion on previous studies, this chapter aims to answer the question of the relationship between the certification effect via CRA's reputation and the bond issuance cost using the above models. The hypothesis are as follows:

> **H1:** Bonds rated by reputable CRAs are associated with significantly lower issuance yield.

According to the results in Chapters 2 and 3, the entry of CCR disciplined the rating behaviour of incumbent issuer-pay CRAs, thus reducing the information asymmetry between the CRA-issuer alliance and investors. This study found that existing issuer-pay CRAs, particularly reputable ones, reduced their rating inflation for firms covered by CCR and their rating changes caused a greater market reaction. Therefore, if the investors are aware of this rating quality change, the entry of CCR should increase the power of the certification effect on CRAs' reputations. This argument can be investigated through Hypotheses H2 and H3.

> **H2:** After CCR's entry, bonds rated by reputable CRAs are associated with an even lower issuance spread.

H3: Compared with CCR-covered firms, reputable CRAs have a greater certification effect on CCR-uncovered firms.

4.2.3 Empirical Literature

There are a number of empirical studies on the certification effect via reputation for investment banks (underwriters). Several researchers discussed the correlation between the reputation of underwriters and the IPO price (Beatty & Ritter 1986; Booth & Smith 1986; Chemmanur & Fulghieri 1994; Hoberg 2007; Johnson & Miller 1988; Loughran & Ritter 2004), but the results were inconclusive. With respect to the bond market, Fang (2005) addressed the importance of underwriters' reputations on the yield of bonds from the perspective of price (underwriting fee) and quality (bond issuance price), revealing that reputable banks obtained lower yields and their underwriting decisions reflected reputation concerns. Fang (2005) also found a positive relationship between reputation and the underwriting fee, consistent with the theory in the product market (Allen 1984; Klein & Leffler 1981; Shapiro 1983). Similarly, Livingston and Miller (2000) and Datta, Iskandar-Datta and Patel (1997) also found a negative relation between an underwriter's reputation and bond yield, but they did not consider self-selection issue. Conversely, Andres, Betzer and Limbach's (2014) results supported the market power hypothesis rather than the certification hypothesis, whereby they found bonds underwritten by the most reputable investment banks were associated with a higher default risk. Employing a high-yield bonds sample, they further found that investors required higher bond yields as they were aware of this higher potential risk.

Regarding the certification role of CRAs, there have been several studies on the certification effect on the stock market for the credit rating industry. For example, Li, Shin and Moore (2006) found that, compared to Japanese rating agencies, international rating agencies, such as Moody's and S&P, have a greater influence on the stock price of Japanese companies. Their findings imply that GRAs have a greater reputation than domestic agencies in Japan, and that this higher reputation affects the stock price change.

With respect to the bond market and the certification role of CRAs, the empirical studies are very rare. Allen and Dudney (2008) analysed the influence of rating agency's reputations on US government bond yields, using the split ratings sample of Moody's and S&P. They found that Moody's impact on bond yields dominated S&P from 1986 to 1994. However, this dominant influence disappeared from 1995 to 2002 following Moody's negative publicity related to an antitrust investigation in 1995. This finding indicated that the reputation change of CRAs was highly related to the investor's willingness to invest in their rated bonds. Livingston, Wei and Zhou (2010) found that issuing rates on split-rated bonds with superior Moody's ratings were about eight bps lower than those given superior ratings by S&P. Their study indicated that investors differentiated between the two ratings and assigned more weight to the ratings from Moody's—the more conservative rating agency.

Moreover, Han, Pagano and Shin (2012) compared the original issuing rate of non-financial Japanese bonds rated by domestic rating agencies to those rated by international agencies from April 1998 to March 2009. They found that the bonds rated by global agencies benefited from 11 to 14 bps yields compared to those rated by domestic CRAs. However, this advantage was offset by the yield increase of 12–17 bps that occurred during the 2007–09 financial crisis for internationally rated bonds. Their results show that the reputation of CRAs plays an important role in determining the financial costs facing bond issuers and that the reputation of international CRAs was damaged during the 2007–2009 financial crisis, which is consistent with the findings of Li, Shin and Moore (2006).

Further, the stronger reputation of international rating agencies can mitigate information asymmetry. Covitz and Harrison (2003) identified that Moody's and S&P changed ratings to protect their reputation as delegated monitors for investors rather than maximising the revenue extracted from issuers. Shin and Moore (2008) concluded that even though Moody's and S&P assigned lower credit ratings to Canadian firms than the Dominion Bond Rating Service (DBRS), a Canadian CRA, the former was more influential in the Canadian capital market.

Additionally, Ferri, Lacitignola and Lee (2013) compared the CARs of the bond market surrounding the rating change announcements issued by the GRA and NRA in Korea. They found that CARs following downgrades by NRAs dominated those by GRAs, which goes against the reputation capital theory that CRAs with a greater reputation capital are more reliable.

There has been limited research on the influence of the reputation of China's CRAs on bond-issuing prices. For a long time, the reputation of issuer-pay CRAs in China was criticised (Kennedy 2008; Lee 2006).

Generally speaking, the empirical studies on the relationship between bond yield and CRA's certification role are still sparse and inconclusive, while the inconclusive evidence mainly stems from the differences in the sample and time period selection. China provides a unique setting in which many issuer-pay CRAs are competing; thus, I have sufficient criteria to split them into reputable and non-reputable groups. The entry of CCR gives us an exogenous shock to further test the certification hypothesis. This thesis complements the literature that supports the certification effect of reputable CRAs in the bond market.

4.3 Sample and Methodology

4.3.1 Sample and Variables

4.3.1.1 Sample

I collected data from Wind, ChinaBond and CCR. The sample consists of 11,845 new bond issuances for 3,344 issuers from 2006 to the end of 2015. The data sample excludes financial institutions bonds, treasury bonds, enterprise set bond, EBs[25] and other non-rated or small volume bond categories.

4.3.1.2 Variables Employed

I estimated the *treasury spread* for every bond issuance, which is defined as the difference between the issue's offering yield and the yield on a benchmark treasury security. This spread, which is also called the risk premium, ultimately measures the default risk of the bond (Fisher 1959) under the assumption that bond yields capture all publicly available information in a timely manner. It is the dependent variable in the regression. The benchmark treasury is chosen as a corresponding China treasury bond with a similar duration and maturity as the bond issuance by the firm in the sample.

My main independent variable is *reputation* that is a dummy variable equal to one if the CRA of the issued bond belongs to the reputable group, zero otherwise. The reputable group consists of CCXI and Lianhe, while the non-reputable group comprises the others. There are three criteria to define whether a CRA belongs to the reputable group: market share, foreign capital and recognition from the government. I applied these criteria, described in Chapters 2 and 3, and recognise CCXI and Lianhe as reputable issuer-pay

[25] The EB market is regulated by CSRC, and joint venture capital CRAs are banned from rating this bond category.

CRAs in China. Thus, *reputation* equals one if the issue is rated by CCXI or Lianhe, zero otherwise.

I also selected several control variables that explained bond yields in terms of issue characteristics based on previous research (Fisher 1959; Fung & Rudd 1986; Horrigan 1966; Kaplan & Urwitz 1979; Sorensen 1979; West 1970; Ziebart & Reiter 1992). The variables are *maturity*, which is the number of years to maturity of debt; *volume*, which is the log of the par value of debt initially issued (in RMB 100 million); *rating*, which is the rating assigned to the debt issuer, based on a notch basis as follows: AAA, AAA– = 5; AA+, AA = 4; AA– = 3; A+ = 2; others = 1; and *enhancement*, which is a dummy variable indicating that the issue has credit enhancements.

In addition to the issue characteristics, I also controlled the following issuer characteristics (Blume, Lim & Mackinlay 1998; Campbell & Taksler 2003): *sales*, which is the log of total sales in RMB 100 million; *leverage*, which is the ratio of total liability from the balance sheet to total assets; *ROA*, which is the return on assets that represents profitability; *tangibility*, which is the ratio of property, plant and equipment to total assets; *growth*, which is the year-to-year increase of operating income; and *cash equivalent*, which is the ratio of cash, tradable asset and receivable over current asset to represent liquidity. Moreover, in all regressions, I controlled economic and industry effects using indicator variables for the years and industries for each issue; ε_i represents the residual.

4.3.2 Methodology

This section analyses the association between the reputation of issuer-pay CRAs and bond yields to see if issuers can save money by hiring reputable CRAs, all things being equal.

To verify the impact of the reputation of CRAs, we assume market investors are sophisticated and can get access to all public information. Thus, the reputation's role is reflected by the treasury spread.

I estimated regressions using Eq. 4.1, in which the treasury spread is the dependent variable and reputation as a dummy variable is the independent variable.

$$Treasury\ Spread_i = c + \beta_1 Reputation_i + \beta_2 Issue\ Characteristics_i + \beta_3 Issuer\ Charateristics_i + \beta_4 X_i + \varepsilon_i \quad (4.1)$$

4.3.2.1 Endogeneity Concerns

From the descriptive statistics in Table 4.1, we observe that issuers rated by reputable CRAs generally have higher ratings (0.238 notches higher), larger scales and greater margins than those rated by non-reputable CRAs. These differences indicate that the matching between a bond issuer and CRA is not a random process. If high-quality firms prefer reputable CRAs, then the lower issuance bond yield may largely depend on the characteristics of issuers, rather than the reputation capital of CRAs. Conversely, if reputable CRAs only choose to rate high-quality firms, then the regression might also overestimate the role of reputation. This may cause endogeneity problems in econometric analysis investigations of the role of reputation by leading to a lower spread in the form of omitted variable bias due to sample selection.

If the unobserved reasons behind reputable CRAs' choices affect the bond yield spread, we may overestimate the certification effect of CRAs' reputations. To correct this problem, we addressed the well-recognised issue of endogenous matching in the Heckman (1980) two-stage 'treatment-regression model' approach (Maddala 1986) in the manner of Guo and Fraser (2014), Ross (2010), Fang (2005) and Andres, Betzer and Limbach (2014).

The appropriate 'treatment effects' model to correct selection bias is

$$\text{Regression equation: } y_i = \beta x_i + \delta w_i + \varepsilon_i \tag{4.2}$$

$$\text{Selection equation: } w^*{}_i = \gamma z_i + \mu_i, w_i = 1 \; if \; w^*{}_i > 0, and \; w_i = 0 \; otherwise \tag{4.3}$$

$$Prob(w_i = 1|z_i) = \Phi(\gamma z_i)$$

and

$$Prob(w_i = 0|z_i) = 1 - \Phi(\gamma z_i)$$

The above models are named 'Heckit' models. These models are direct applications of the sample selection model used to estimate 'treatment effects' in observational studies. The 'treatment effects' model differs from the sample selection model in two ways: 1) a dummy variable indicating the treatment conditions w_i (i.e., $w_i = 1$ if observation i is in the treatment regime, zero otherwise) directly entered into the regression equation, and 2) the outcome variable is observed for both regimes (i.e., $w_i = 1$ and $w_i = 0$).

The evaluation task is to use the observed variables to estimate the regression coefficients $\beta$and the 'treatment effects' δ, while controlling for selection bias induced by non-random treatment assignment. The model expressed by Eq. 4.2 and Eq. 4.3 is a switching regression. By substituting w_i in Eq. 4.2 with Eq. 4.3, we obtain two different equations of the outcome regression:

$$\text{when } {w^*}_i > 0, w_i = 1: y_i = \beta x_i + \delta(\gamma z_i + \mu_i) + \varepsilon_i \tag{4.4}$$

and

$$\text{when } {w^*}_i \leq 0, w_i = 0: y_i = \beta x_i + \varepsilon_i \tag{4.5}$$

This is Quandt's (1958) form of the switching regression model that indicates two regimes for treatment and non-treatment groups. Eq. 4.4 is the outcome model for treated observations, whereas Eq. 4.5 is for non-treated participants.

A consistent two-step approach for this model was suggested by Maddala (1986), which is referred to as the dummy endogenous regression model with a structural shift. In the first stage, predicted values for Pr(w=1|z) from a probit model is obtained, and a hazard variable (see Eq. 4.6) representing the unobserved variables is calculated and included as an additional regressor in a regression model in the second stage (Powers 2007).[26]

$$h_i = \begin{cases} \emptyset(\hat{\gamma} z_i)/\Phi(\hat{\gamma} z_i) & w_i = 1 \\ -\emptyset(\hat{\gamma} z_i)/\{1 - \Phi(\hat{\gamma} z_i)\} & w_i = 0 \end{cases} \tag{4.6}$$

where $\emptyset$ is the standard normal density function.

For this study, in the first stage of the Heckman approach, it estimated selection equations for issues' and firms' characteristics leading to the rating of reputable CRAs using Eq. 4.7. Following the literature regarding the independent variables for CRA selection equations, I controlled all the issue levels and firm-level characteristics in the first-stage regression. Aside from the variables in the second-stage regression, at least some of the variables should be valid instruments in the first stage in the sense that they are not only meaningful predictors of the likelihood that reputation equals one but also independent of the bond yield and thus properly excludable from the second-stage regression (Prabhala & Li 2007). According to Fang (2005), total issue times (*frequency*) is used as the main instrument for CRA selection. *Frequency* is the number of bond

[26] We also employed the one-step maximum likelihood estimation (ML); the results are qualitatively unchanged.

issues conducted by the firm during 2006 to 2015. As the rating business is a repeat behaviour, the willingness to keep repeat clients is the main drive behind why CRAs want to keep a good reputation. Thus, reputable CRAs like to choose repeat issuers. However, repeat issuers have less financial constraints as they can repeatedly issue bonds publicly compared to other issuers. To save issue costs (including the communication cost with CRAs), they also have more incentives to choose reputable CRAs. Column 4 of Table 4.2 presents the underlying reputable CRA-issue matching equation. *Frequency* is highly statistically significant and positively associated with the probability of being rated by reputable CRAs, confirming the existence of selection bias. The IVs should not be related to the particular issuance price for each issue, because the market will not lower the spreads simply because the company issues more bonds. I then add the hazard variable that is calculated from the predicted value of *reputation* from the first-stage regression to the second-stage regression using Eq. 4.8 to find the true effect of CRAs' reputations on bond issuance yield. Year fixed effects and industry fixed effects are considered in both regressions, although the results are not reported.

$$Reputation_i = \gamma_1 Issue\ Characteristics_i + \gamma_2 Issuer\ Characteristics_i + \gamma_3 X_i + \gamma_4 Frequency_i + v_i \tag{4.7}$$

$$Treasury\ Spread_i = c + \beta_1 Reputation_i + \beta_2 Issue\ Characteristics_i + \beta_3 Issuer\ Characteristics_i + \beta_4 X_i + \beta_5 Hazard_i + \varepsilon_i \tag{4.8}$$

4.4 Empirical Results

4.4.1 Descriptive Statistics

Table 4.1 presents the summary statistics for the overall sample (Panel A) and comparisons between bonds rated by reputable CRAs and non-reputable CRAs (Panel B). Results of t-test for differences in means and medians between the two subsamples are reported in the last two rows.

With respect to the main bond characteristics, it reports a mean treasury spread of 2.379% for the bonds in the full sample, a mean issue volume of RMB 849 million, a mean time to maturity of 3.345 years, and a mean issuer's rating of 3.940 (below AA). The mean and median differences show that issues rated by reputable CRAs, as compared to non-reputable CRAs, are significantly larger in terms of issuance volume (RMB 940 million v. RMB 749 million) and shorter in terms of maturity (3.029 years v. 3.733 years). In addition, on average, bonds rated by reputable CRAs have a significantly lower treasury spread (2.170% v. 2.635%) and higher issuer's rating (4.047 v. 3.809) than those rated by non-reputable ones.

Turning to the issuers' characteristics, issuers rated by reputable CRAs are significantly larger in terms of sales, more leveraged and profitable, and have more tangible assets than their counterparts rated by non-reputable CRAs. Moreover, on average, issuers rated by reputable CRAs issue more frequently on the bond market (10 times v. 6.52 times during a 10-year sample period).

The above comparison between the most important bond and issuer characteristics reveal significant disparities between bonds rated by reputable CRAs and those rated by CRAs with a lesser reputation. These differences are consistent with the differences reported in Allen and Dudney (2008) and Han, Pagano and Shin (2012). The well-recognised issue of selection in the rating process is thus apparent in the data, just as addressed in Section 4.3.2.

4.4.2 Baseline Empirical Results

In this section, I attempt to answer the research question of whether certification via reputation of CRAs is beneficial or detrimental to bond issuers. In particular, I test the first hypothesis (H1) as presented in Section 4.3.2. Specifically, I run the regressions in the form of Eq. 4.1 to test if bonds rated by reputable CRAs have a lower issuance yield, or if reputable CRAs can certify the bonds' quality. If we observe a significantly negative value of the coefficient on reputation, then ceteris paribus, employing more reputable CRAs can save issuance costs for issuers. I also control the sample selection bias described in Section 4.3.2.

From the raw sample results in Table 4.2, we observe a significantly negative coefficient of reputation. For instance, in Model 3, bonds rated by CCXI or Lianhe have a 0.160% lower treasury spread than bonds rated by less reputable CRAs, all else being equal. In practice, issuers can save more than RMB 1.2 million per year on average by hiring reputable CRAs. Moreover, the signs on the other variables are in line with this expectation. For example, we observe that the issuer's rating term is negative, indicating that higher yields are required from bonds with lower (worse) ratings, which is in line with intuition and basic economic theory (Fisher 1959).

Columns 4 to 7 present the results when controlling endogeneity and applying the Heckman two-stage 'endogenous treatment-regression' model. From the bond-reputable CRA matching result from Column 4, we observe similar patterns shown in the univariate test from Table 4.1. Generally speaking, bonds with a shorter maturity, higher issuer rating, larger size, higher leverage, lower tangibility and higher earning ability are likely to choose more reputable CRAs. Further, issuers who frequently issue bonds are more likely to be chosen by reputable CRAs. After controlling the sample selection bias, we observe similar results from Columns 5 to 7 of Table 4.2 that show that issuers hiring reputable CRAs to rate their bonds can save bond spread significantly. For example, in Column 7, the difference between bond issuance yield and treasury yield is 0.380% lower in bonds rated by reputable CRAs, all else being equal. Column 8 shows us that the IV frequency chosen is independent from the dependent variable.

The results in Table 4.2 suggest that the certification role of CRAs via reputation works in China's bond market, even after controlling the sample selection bias.

4.4.3 An Analysis Conditional on the Investor Protection Environment and Issuer's Risk

In this section, this research find the mechanisms through which reputable CRAs implement their certification effect on issuers.

4.4.3.1 Certification Effect Conditional on the Investor Protection Environment

As an information provider, reputable CRAs' certification value is expected to have a greater effect for issuers with a bad investor protection environment. Investors can access information through more channels if the issuers are exposed to the public; thus, the information source is not restricted to CRAs' ratings. However, for firms with little exposure to the public, CRAs' rating reports becomes an essential way to get information to issuers, and investors of bond issuers who have a bad investor protection environment are more likely to rely on CRAs.

Therefore, this study hypothesises that issuers with a worse investor protection environment can save more treasury spread when hiring reputable CRAs. To test this hypothesis, I performed an analysis conditional on an issuer's investor protection environment. Here, I used IPI to capture the investor protection environment.

IPI was developed by Fan, Wang and Zhu (2011) to show the maturity of the market for each province in China, just as described in Chapter 2. I classified an issuer as having a better investor protection environment if it came from a province where the IPI is above the sample median. The high IPI group consists of firms who come from provinces with an IPI above the median level; otherwise the company belongs to the low IPI group.

From Table 4.3, for both groups, hiring reputable CRAs is generally associated with a lower treasury spread. However, when I look at the coefficient differences between the two groups, I find the value is significantly negative. The coefficient difference is -0.056, which means compared with firms with better investor protection environment, firms with worse investor protection environment on average can save 0.056% more when hiring reputable CRAs. These results indicate that the certification role of reputable CRAs are more valued by investors of bond issuers who have a bad investor protection environment.

4.4.3.2 Certification Effect Conditional on Issuer's Risk

Another mechanism I consider is issuer's risk: investors put more trust in ratings by reputable CRAs for issuers with a higher default risk. Thus, all things being equal, investors require less return for bonds rated by reputable CRAs, especially for high-risk issuers. Therefore, I used two variables to measure the risk of issuers. The first measure is the size of the issuers. In China, large-sized companies can more easily get access to funds from the market or government. Generally speaking, the larger the size, the safer the security. The second measure is the rating of issuers. If the issuer's rating is below the sample median level, then it belongs to the high-risk group as the ratings represent the default risk.

From Table 4.3, I observe that for small issuers and low-rating issuers, hiring reputable CRAs can reduce treasure spread. This indicates that the certification effect of reputable CRAs is stronger for issuers with high risk.

Table 4.1: Rating Sample Summary Statistics

Table 4.1 presents descriptive statistics for bond issues from 2006 to 2015. Panel A presents the statistics of the full sample. Treasury spread is the difference between the issue's offering yield and the yield on a benchmark treasury security. The benchmark treasury is chosen as a corresponding China treasury bond with a similar duration and maturity as that expressed in the bond issuance by the firm in the sample. Maturity is the number of years to maturity of debt; volume is the log of the par value of debt initially issued (in RMB 100 million); rating is a numerical value of ratings assigned on the issuers, based on a notch basis as follows: AAA, AAA– = 5, AA, AA = 4, AA– = 3, A+ = 2, others = 1; enhancement is a dummy variable indicating the issue has credit enhancements; assets and sales are the log of total assets and sales in RMB 100 million; leverage is the ratio of total liability from the balance sheet to total assets; ROA is the return on assets that represents profitability; tangibility is the ratio of property, plant and equipment to total assets; growth is the year-to-year increase of operating income; all above variables are measured at the time t-1. Frequency is the number of bond issues the firm conducts during the 10-year sample period. Cash equivalent is the ratio of cash, tradable asset and receivable over current asset to represent liquidity. Panel B presents the statistics of reputable and non-reputable groups and the mean differences between these two groups. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels respectively.

Panel A: Summary statistics of full sample													
		Treasury spread	Maturity	Volume	Rating	Enhancement	Sales	Leverage	Tangibility	ROA	Growth	Frequency	Cash equivalent
Whole sample	Mean	2.379	3.345	2.139	3.940	0.114	4.258	0.586	0.247	5.362	0.432	8.440	0.466
	Std.dev.	1.011	2.833	0.890	0.765	0.317	1.878	0.163	0.206	11.934	7.579	8.568	1.704
	Min.	–4.100	0.240	–2.303	1	0	–3.912	0.001	0	–25.678	–0.999	1	0.000
	Max.	6.666	23	5.704	5	1	10.215	0.977	0.969	861.116	541.278	62	100.018
	N	11,845	11,845	11,844	11,845	11,845	11,800	11,808	11,779	11,791	11,779	11,845	11,792
Panel B: Summary statistics of reputable and non-reputable samples													
Bond rated by reputable CRAs	Mean	2.170	3.029	2.241	4.047	0.081	4.653	0.605	0.265	5.768	0.410	10.009	0.461
	Std.dev.	0.934	2.727	0.928	0.776	0.272	1.831	0.154	0.207	15.645	7.267	9.210	1.539
	Min.	–4.100	0.240	–2.303	1	0	–3.219	0.001	0	–13.319	–0.990	1	0.001
	Max.	6.402	20	5.704	5	1	10.215	0.977	0.969	861.116	541.278	62	100.018
	N	6519	6519	6518	6519	6519	6489	6492	6485	6476	6474	6519	6476
Bond rated by non-reputable CRAs	Mean	2.635	3.733	2.014	3.809	0.154	3.776	0.563	0.225	4.867	0.459	6.520	0.472
	Std.dev.	1.042	2.913	0.825	0.729	0.361	1.821	0.170	0.203	4.163	7.944	7.263	1.887
	Min.	–1.027	0.250	–1.609	1	0	–3.912	0.003	0	–25.678	–0.999	1	0.000
	Max.	6.666	23	5.298	5	1	10.078	0.926	0.946	38.546	537.077	62	88.378
	N	5326	5326	5326	5326	5326	5311	5316	5294	5315	5305	5326	5316
Mean difference		–0.465***	–0.704***	0.227***	0.238***	–0.073***	0.877***	0.042***	0.040***	0.901***	–0.049	3.489***	–0.111
Median difference		–0.492***	–2***	0.224***	0	0	0.946***	0.042***	0.046***	0.805***	0.010**	3***	0.006

Table 4.2: Bond Issuance Yield and Reputation of Credit Rating Agencies

Table 4.2 presents the relationship between bond issuance yield and the reputation of CRAs. The sample consists of 11,845 issuance observations for 3344 issuers from 2006 to the end of 2015. Columns 1 to 3 present the results for Eq. 4.1 using the raw sample. All variables are the same as Table 4.1. The Heckman sample shows results when considering sample selection bias using the two-stage treatment-effect method. Column 4 presents results for the first-stage bond-reputable CRA matching equation, and the left-hand variable is reputation. Frequency is the number of bond issues the firm conducts during the 10-year sample period. Columns 5 to 7 present results for the second-stage regression. Industry fixed effects are indicator variables for industry of the issuer; year fixed effects are indicator variables for fiscal years. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels respectively.

	Raw sample			Heckman sample				
				First stage	Second stage			
	(1)	(2)	(3)	Reputation (4)	(5)	(6)	(7)	(8)
Reputation	–0.175***	–0.230***	–0.160***		–1.284***	–3.160***	–0.380**	
	(0.014)	(0.016)	(0.014)		(0.119)	(0.223)	(0.168)	
Maturity	0.068***		0.058***	–0.042***	0.043***		0.054***	0.060***
	(0.003)		(0.003)	(0.005)	(0.005)		(0.004)	(0.003)
Volume	–0.018*		0.031***	0.063***	0.036**		0.036***	0.030***
	(0.010)		(0.011)	(0.019)	(0.014)		(0.012)	(0.011)
Issuer's rating	–0.705***		–0.639***	0.107***	–0.615***		–0.629***	–0.649***
	(0.012)		(0.013)	(0.021)	(0.018)		(0.015)	(0.013)
Enhancement	–0.134***		–0.159***	–0.073*	–0.191***		–0.167***	–0.151***
	(0.025)		(0.025)	(0.044)	(0.032)		(0.026)	(0.025)
Sales		–0.229***	–0.072***	0.055***		–0.057***	–0.064***	–0.076***
		(0.005)	(0.006)	(0.011)		(0.016)	(0.009)	(0.007)
Leverage		0.004***	0.001*	0.003***		0.005***	0.001*	0.001
		(0.001)	(0.001)	(0.001)		(0.001)	(0.001)	(0.001)
Tangibility		–0.292***	–0.215***	-0.005		–0.155*	–0.209***	–0.203***

		(0.047)	(0.043)	(0.063)		(0.086)	(0.043)	(0.043)
ROA		0.000	–0.000	0.019***		0.003***	0.000	–0.000
		(0.001)	(0.001)	(0.003)		(0.001)	(0.001)	(0.001)
Growth		0.001	0.001	0.001		0.003	0.001	0.001
		(0.001)	(0.001)	(0.002)		(0.002)	(0.001)	(0.001)
Cash equivalent		–0.012***	–0.008*	0.015**		0.006	-0.006	–0.009**
		(0.004)	(0.004)	(0.007)		(0.009)	(0.004)	(0.004)
Frequency				0.015***				–0.000
				(0.002)				(0.001)
Constant	3.866***	2.248***	3.864***	–0.926***	4.116***	3.079***	3.909***	3.813***
	(0.067)	(0.071)	(0.074)	(0.088)	(0.078)	(0.117)	(0.082)	(0.074)
Hazard					0.694***	1.835***	0.136	
					(0.073)	(0.138)	(0.104)	
Observations	11,844	11,735	11,734	11,734	11,734	11,734	11,734	11,734
R-squared (Pseudo R2)	0.468	0.355	0.475	0.056				0.469
Prob > chi2				0.000	0.000	0.000	0.000	
Industry and year fixed effects	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes

Table 4.3: Certification Effect Conditional on the Investor Protection Environment and Issuer's Risk

Table 4.3 presents the certification effect, classified by issuer's investor protection environment and issuer's risk. The sample consists of 11,845 issuance observations for 3344 issuers from 2006 to the end of 2015. The left-hand variable is treasury spread. All the variables are the same as those in Table 4.2. The results already consider sample selection bias using the two-stage treatment-effect method. We classify an issuer as having a better investor protection environment if it comes from the province where the IPI is above the sample median. The high IPI group consists of firm who come from provinces with an IPI above the median level; otherwise the company belongs to the low IPI group. We use size and rating levels to measure the risk of issuers. Issuers with lower than sample median sales and issuers who have lower than median ratings belong to the high-risk group; otherwise they belong to the low-risk group. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels respectively.

	Investor protection environment		Issuer's risk			
	Investor protection index		Size		Rating level	
	Low IPI (0)	High IPI (1)	Small (0)	Large (1)	Low (0)	High (1)
Reputable	–0.189***	–0.133***	–0.188***	–0.101***	–0.164***	–0.063***
	(0.021)	(0.021)	(0.022)	(0.019)	(0.021)	(0.017)
Difference (0) – (1)	–0.056*	Chi2 = 3.67	–0.087**	Chi2 = 9.1	–0.101***	Chi2 = 14.14
Maturity	0.059***	0.038***	0.082***	0.033***	–0.074***	0.006
	(0.009)	(0.005)	(0.012)	(0.004)	(0.008)	(0.004)
Volume	0.083***	0.013	0.038	–0.022	0.253***	0.027**
	(0.021)	(0.015)	(0.027)	(0.014)	(0.024)	(0.012)
Issuer's rating	–0.608***	–0.616***	–0.665***	–0.613***		
	(0.029)	(0.023)	(0.036)	(0.021)		
Enhancement	–0.176***	–0.229***	–0.248***	–0.214***	–0.511***	–0.313***
	(0.036)	(0.044)	(0.038)	(0.045)	(0.034)	(0.047)
Sales	–0.042***	–0.052***	–0.058***	–0.064***	0.216***	–0.053***
	(0.015)	(0.011)	(0.020)	(0.012)	(0.015)	(0.010)

Leverage	0.002*	0.002**	0.000	0.004***	0.012***	0.008***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Tangibility	–0.165***	–0.366***	–0.254***	–0.104*	–0.158**	0.004
	(0.058)	(0.060)	(0.060)	(0.059)	(0.063)	(0.047)
ROA	0.007**	0.000	0.009*	–0.000	0.070***	0.000**
	(0.004)	(0.000)	(0.004)	(0.000)	(0.004)	(0.000)
Growth	0.002***	0.002	0.001**	–0.007	0.005***	–0.003
	(0.000)	(0.009)	(0.000)	(0.015)	(0.001)	(0.006)
Cash equivalent	–0.003	–0.050	–0.007	0.004	0.045***	0.027**
	(0.004)	(0.047)	(0.005)	(0.038)	(0.005)	(0.012)
Hazard	0.538**	0.202	0.237	–0.040	5.459***	0.917***
	(0.241)	(0.137)	(0.333)	(0.132)	(0.204)	(0.107)
Constant	2.776***	3.905***	3.423***	3.966***	-4.594***	0.504***
	(0.349)	(0.204)	(0.471)	(0.195)	(0.264)	(0.142)
Observations	5967	5767	5847	5887	6927	4807
R-squared (adjusted)	0.427	0.510	0.450	0.434	0.347	0.303
Industry and year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

4.5 Empirical Results Conditional on the Entry of China Credit Rating

4.5.1 Certification Comparison Before and After China Credit Rating's Entry

To test H2, I needed to define a new variable *post*, which is a dummy equal to one if the bond issuance date is after 2012 when CCR officially started its rating business, otherwise zero. Panel A of Table 4.4 shows the univariate test results for the certification effect change before and after CCR's entry. From Panel A, we observe that during the pre-period, the treasury spread of bonds rated by reputable CRAs is 0.328% lower than bonds rated by non-reputable CRAs on average, and this difference is even larger during the post-period at 0.461%.

I then added other control variables and estimated the certification change using Eq. 4.9. If a significantly negative value for β_1 is observed, this means that after the entry of CCR, bonds rated by reputable CRAs enjoy an even lower issuing spread than bonds rated by non-reputable CRAs. In turn, the certification effect of reputable CRAs is more valued by investors after CCR's entry because CCR's intervention increases the rating quality of existing CRAs, particularly for reputable ones.

$$Treasury\ Spread_i = c + \beta_1 Reputation_i \times Post_i + \beta_2 Reputation_i + \beta_3 Post_i + \beta_4 Issue\ Characteristics_i + \beta_5 Issuer\ Characteristics_i + \beta_6 X_i + \varepsilon_i \qquad (4.9)$$

From Panel B of Table 4.4, after I control year fixed effects, industry fixed effects and other issue and issuer-related control variables respectively, we observe a significantly negative value of the coefficient of the interaction term. For example, in Column 3, the value of β_1 is –0.095; this means employing reputable CRAs can save 0.095% more on the treasury spread during the post-period compared with the pre-period. Moreover, the economic value is significant and, on average, the cost saving per year by reputable CRAs is around RMB 0.8 million larger during the post-period than the pre-period.

I also applied the Heckman method described in Section 4.3.2. The results are presented in Columns 4 and 5 of Table 4.4, and show that the results are qualitatively unchanged. Thus, this research found that issuers hiring reputable CRAs can save more treasury spread after CCR's entry.

4.5.2 Certification Effect Comparison between China Credit Rating-Covered and Uncovered Issuers

I use Eq. 4.10 to investigate H3, in which *CCRcover* is a new variable that equals one if the bond issuer is covered by CCR between 2012 and 2015, otherwise zero. The estimation period is from 2012 to 2015, which is the period after CCR's entry. There are 8,261 observations for 3,019 issuers during this period, among which 814 issuers are coved by CCR. In Eq. 4.10, β_1 represents the spread saving difference caused by the certification effect between CCR-covered and CCR-uncovered issuers. As CCR's entry disciplines rating behaviour and increases the informativeness of existing issuer-pay CRAs, particularly reputable CRAs, the certification effect on reducing treasury spread by reputable CRAs is expected to be greater for uncovered issuers. Therefore, we should observe a significantly positive value for β_1 that indicates that the treasury spread saved by hiring reputable CRAs is greater for CCR-uncovered issuers.

$$Treasury\ Spread_i = c + \beta_1 Reputation_i \times CCRcover_i + \beta_2 Reputation_i + \beta_3 CCRcover_i + \beta_4 Issue\ Characteristics_i + \beta_5 Issuer\ Characteristics_i + \beta_6 X_i + \varepsilon_i \tag{4.10}$$

Table 4.4: Certification Effect Change Before and After China Credit Rating's Entry

Table 4.4 presents the certification effect change before and after CCR's entry. The sample consists of 11,845 issuance observations for 3344 issuers from 2006 to the end of 2015. Panel A shows the univariate test results. Panel B presents the multivariate test results. Columns 1 to 3 present the results for Eq. 9 using the raw sample. The left-hand variable is the treasury spread. All the variables are the same as those in Table 4.2 except post, which equals one if the bond issuance date is after 2012, zero otherwise. The Heckman sample shows results when considering sample selection bias using the two-stage treatment-effect method. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels respectively.

Panel A: Univariate test

		(1) Pre	(2) Post	Difference (2) – (1)
(3)	Reputable = 0	Obs = 1331	Obs = 4037	
		2.304***	2.734***	0.431***
		(0.029)	(0.015)	(0.033)
(4)	Reputable = 1	Obs = 2307	Obs = 4234	
		1.976***	2.273***	0.297***
		(0.019)	(0.014)	(0.024)
	Difference (4) – (3)	–0.328***	–0.461***	
		(0.033)	(0.021)	

Panel B: Multivariate test

	Raw sample			Heckman sample	
				First stage	Second stage
	(1)	(2)	(3)	(4) Reputation	(5)
Reputation*Post	–0.079**	–0.129***	–0.095***		–0.127***
	(0.039)	(0.031)	(0.033)		(0.031)
Reputation	–0.320***	–0.068***	–0.112***		–0.252
	(0.033)	(0.026)	(0.028)		(0.170)
Post	0.334***		0.443***		
	(0.031)		(0.027)		
Maturity		0.058***	0.060***	–0.042***	0.055***
		(0.003)	(0.003)	(0.005)	(0.004)
Volume		0.032***	0.011	0.063***	0.036***
		(0.011)	(0.012)	(0.019)	(0.012)
Issuer's rating		–0.639***	–0.597***	0.107***	–0.631***
		(0.013)	(0.014)	(0.021)	(0.015)
Enhancement		–0.157***	–0.195***	–0.073*	–0.164***
		(0.025)	(0.027)	(0.044)	(0.026)
Sales		–0.073***	–0.071***	0.055***	–0.066***
		(0.006)	(0.007)	(0.011)	(0.009)
Leverage		0.001*	0.000	0.003***	0.001**
		(0.001)	(0.001)	(0.001)	(0.001)
Tangibility		–0.213***	–0.364***	–0.005	–0.208***
		(0.043)	(0.046)	(0.063)	(0.043)
ROA		–0.000	0.000	0.019***	0.000
		(0.001)	(0.001)	(0.003)	(0.001)
Growth		0.001	0.002**	0.001	0.001
		(0.001)	(0.001)	(0.002)	(0.001)
Cash equivalent		–0.008*	–0.008*	0.015**	–0.007

		(0.004)	(0.004)	(0.007)	(0.004)
Frequency				0.015***	
				(0.002)	
Constant	2.050***	3.799***	4.543***	–0.926***	3.837***
	(0.038)	(0.076)	(0.063)	(0.088)	(0.083)
Hazard					0.113
					(0.104)
Observations	11,845	11,734	11,734	11,734	11,734
R-squared (pseudo R2)	0.129	0.476	0.374	0.056	
Prob > chi2				0.000	0.000
Industry fixed effects	Yes	Yes	Yes	No	Yes
Year fixed effects	No	Yes	No	No	Yes

Table 4.5 presents the results for comparison between these two groups. Panel A shows the univariate result that for uncovered issuers, hiring reputable CRAs can have a 0.454% lower treasury spread, while for covered issuers, the spread saving is only 0.215%, 0.239% less than uncovered issuers. This means that, on average, the certification effect of reputable CRAs on saving issuing costs is stronger for uncovered firms. Panel B presents the multivariate result. For the four models of the raw sample and Heckman sample, we observe a significantly positive value for β_1. In Model 4, for example, the spread saving by hiring reputable CRAs for CCR-uncovered issuers is 0.181% greater than covered issuers, which means, on average, keep other things unchanged, if hiring reputable CRAs, CCR-uncovered issuers can save approximately RMB 1.8 million more per year than CCR-covered issuers.

This may be because the certification effect of reputable CRAs is reinforced by CCR’s entry. Specifically, as long as there is no third-party intervention (no CCR’s coverage), investors are more likely to believe in reputable CRAs, as their rating quality has been indirectly raised by CCR’s entry. This is also consistent with the findings in Chapters 2 and 3. This result also reveals that the reputational mechanism works in China and supplements previous studies.

Therefore, through estimations of H2 and H3, this study found that the certification effect of reputable CRAs was enhanced by the entry of CCR.

Table 4.5: Certification Effect Comparison between China Credit Rating-Covered and China Credit Rating-Uncovered Issuers

Table 4.5 presents the certification effect change before and after CCR's entry. The sample consists of 8261 issuance observations for 3019 issuers from 2012 to the end of 2015. There are 814 firms covered by CCR. Panel A shows the univariate test results. Panel B presents the multivariate test results. Columns 1 to 4 present the results for Eq. 10 using the raw sample. The left-hand variable is the treasury spread. All the variables are the same as those in Table 4.2 except CCRcover that equals one if the bond issuer is covered by CCR, zero otherwise. The Heckman sample shows results when considering sample selection bias using the two-stage treatment-effect method. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels respectively.

Panel A: Univariate test

		(1) CCRcover = 0	(2) CCRcover = 1	Difference (2) – (1)
(3)	Reputable = 0	Obs = 2480	Obs = 1554	
		3.010***	2.294***	–0.716***
		(0.020)	(0.022)	(0.031)
(4)	Reputable = 1	Obs = 1720	Obs = 2507	
		2.556***	2.079***	–0.477***
		(0.025)	(0.016)	(0.028)
	Difference (4) – (3)	–0.454***	–0.215***	
		(0.032)	(0.027)	

Panel B: Multivariate test

	Raw sample				Heckman sample	
	(1)	(2)	(3)	(4)	First stage (5)	Second stage (6)
Reputation*CCRcover	0.245***	0.188***	0.212***	0.181***		0.181***
	(0.039)	(0.033)	(0.038)	(0.033)		(0.033)
Reputation	–0.418***	–0.250***	–0.342***	–0.243***		–0.230
	(0.027)	(0.023)	(0.027)	(0.023)		(0.214)
CCRcover	–0.716***	–0.208***	–0.426***	–0.176***		–0.176***
	(0.029)	(0.026)	(0.030)	(0.027)		(0.027)
Maturity		0.087***		0.084***	–0.057***	0.084***
		(0.004)		(0.004)	(0.007)	(0.006)
Volume		0.016		0.043***	0.024	0.043***
		(0.013)		(0.013)	(0.024)	(0.013)
Issuer's rating		–0.879***		–0.849***	0.260***	–0.850***
		(0.017)		(0.018)	(0.030)	(0.027)
Enhancement		–0.206***		–0.206***	–0.168***	–0.205***
		(0.030)		(0.031)	(0.056)	(0.034)
Sales			–0.197***	–0.047***	0.029**	–0.047***
			(0.007)	(0.008)	(0.013)	(0.010)
Leverage			0.005***	0.002***	0.003***	0.002***
			(0.001)	(0.001)	(0.001)	(0.001)
Tangibility			–0.242***	–0.124**	–0.176**	–0.124**
			(0.059)	(0.051)	(0.078)	(0.052)
ROA			0.000	–0.000	0.018***	–0.000
			(0.001)	(0.001)	(0.004)	(0.001)
Growth			–0.001	–0.002	0.002	–0.002
			(0.004)	(0.004)	(0.006)	(0.004)

Cash equivalent			–0.012**	–0.006	0.008	–0.006
			(0.006)	(0.005)	(0.008)	(0.005)
Frequency					0.016***	
					(0.003)	
Constant	3.086***	5.894***	3.408***	5.790***	–1.336***	5.790***
	(0.042)	(0.065)	(0.053)	(0.074)	(0.118)	(0.074)
Hazard						–0.008
						(0.131)
Observations	8261	8261	8209	8209	8209	8209
R-squared (pseudo R2)	0.246	0.474	0.314	0.477	0.063	
Prob > chi2					0.000	0.000
Industry and year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

4.6 Robustness Test

4.6.1 Additional Rating Scale and Additional Test for Bonds in Each Year

I estimated the relationship between the bond issuance yield and reputation of CRAs for each rating scale from 1 to 5. Except for the scale of AAA and the very low ratings (scale 1), the results are qualitatively unchanged for all other rating scales. In regard to AAA issuers, who have the highest rating, investors do not strongly take into consideration who rated them (see Appendix 4.1).

Furthermore, this thesis estimated the relationship between the bond issuance yield and reputation of CRAs for each particular issuance year from 2006 to 2015 respectively. The results are qualitatively unchanged (see Appendix 4.2).

4.6.2 Additional Test on the Maturity and Categories of Bonds

I divided all bonds into three categories according to their maturity length. Category 1 is short-term bonds whose maturity is less than three years; category 2 is medium-term bonds with maturity between three and five years; category 3 is long-term bonds whose maturity length is over five years. I then tested the relationship between the bond issuance yield and reputation of CRAs for each category. The results are qualitatively unchanged (see Appendix 4.3).

Moreover, according to the bond category, I further estimated the relationship between the bond issuance yield and reputation of CRAs for each type of bond: CPs, MTNs and CBs. The results are qualitatively unchanged for all types of bonds (see Appendix 4.4).

4.6.3 Propensity Score Matching Sample to Control Selection Bias of China Credit Rating's Coverage

To control the potential problem of sample selection bias of CCR's coverage, I applied the PSM method to match out the most similar firms from the uncovered group each year from 2012 to 2015. Using the PSM sample, I compared the certification effect of reputable CRAs between CCR-covered firms and uncovered firms. The results are qualitatively unchanged (see Appendix 4.5).

4.6.4 Propensity Score Matching Method to Remedy Endogeneity of Reputable China Credit Rating's Coverage

Along with the Heckman two-stage model, I also applied the PSM method to match out the most similar bonds from the non-reputable CRA-rated group each year from 2006 to 2015. I still found that compared with bonds rated by reputable CRAs, those bonds that were rated by non-reputable CRAs but have the most similar firm characteristics needed to pay more default spread, keeping all other control variables the same. This reflects the certification effect of reputable CRAs as well (see Appendix 4.6).

4.7 Conclusion

This chapter provides evidence of the role and value of certification by reputable CRAs in China. On average, issuers employing reputable CRAs have a lower treasury spread when issuing new bonds. Even after controlling the sample selection bias and other control variables, I still find the same results. This is in line with Han, Pagano and Shin (2012) and Li, Shin and Moore (2006) in that investors require risk premium on bonds rated by non-reputable CRAs. In addition, the investor protection environment and issuer's risk are found to be two mechanisms through which the certification effect can benefit issuers.

Further, I find that this certification effect is enhanced by CCR's entry, which reduced rating inflation and increased the rating informativeness of existing issuer-pay CRAs in China, particularly for reputable CRAs. After CCR's entry, hiring reputable CRAs can save more treasury spread, which shows that the certification role of reputable CRAs is more valued by investors as their rating behaviour is disciplined by CCR. Moreover, for CCR-uncovered issuers, using reputable CRAs is associated with a greater spread saving. This demonstrates that after CCR's entry, investors want to trust reputable

CRAs when there is no rating by CCR; in turn, this verifies the important role of CCR. These findings supplement the existing literature on the certification effect of CRAs, particularly in emerging markets.

Chapter 5
Summary and Contributions

With increased criticism of CRAs' rating quality, academics and governments have proposed several alternative models to replace the issuer-pay business model of incumbent CRAs. China provides us with a unique opportunity to analyse how the entry of CCR, a new independent CRA that utilises a combination of public utility and investor-pay models, affects the behaviour of incumbent issuer-pay CRAs in China.

5.1 Summary

5.1.1 Results from Difference-in-Differences Analysis on Credit Ratings

In Chapter 2, I used the rating data from 2006 to 2015 in China to analyse the rating change. Through a DID study, I found a decline in rating inflation (ratings from issuer-pay CRAs) for firms covered by CCR, compared with those not covered by CCR. This result indicates the rating strategy change of incumbent CRAs, The Heckman two-stage method and PSM method were employed to control the endogeneity problem and the results were qualitatively unchanged.

Thus, CCR acts in a certification role to discipline incumbent issuer-pay CRAs and creates a benchmark for them. In particular, this discipline effect is more significant in more reputable issuer-pay CRAs and firms with a better investor protection environment. I further found that reputational mechanism and public supervision were two mechanisms through which CCR's entry influenced incumbent issuer-pay CRAs' rating behaviour.

5.1.2 Results from Analysis on Event Study

In Chapter 3, I examined how the entry of CCR affected the information content of rating changes by incumbent issuer-pay CRAs in China. By comparing the market reaction following rating changes before and after CCR's coverage initiation, I found there was a significant improvement in the rating quality of incumbent CRAs. Their ratings incorporated greater information content that triggered a greater market reaction to their rating downgrade announcements following CCR's coverage. Subsequently, I employed the IV approach and PSM method to remedy the possible endogeneity issue, establishing the causal role of CCR's coverage initiation. I further found that all ratings of incumbent CRAs were lower than CCR's, and only the downgrades caused greater reactions during the post-coverage period. This unbalanced market reaction between downgrades and upgrades suggests a rating strategy adjustment by incumbent CRAs in response to the reputational mechanism elevated by CCR's entry. Next, this research found that CCR's entry had a greater effect on more reputable issuer-pay CRAs, and a greater influence on issuers with a better investor protection environment. This finding indicates that incumbent CRAs' rating behaviour can be disciplined by CCR's entry through their own reputation concerns and outside monitors.

5.1.3 Results from Analysis on Certification through Reputation

In Chapter 4, this research investigates the value of certification provided by relatively more reputable credit rating agencies. This thesis provides evidence of the role and value of certification by reputable CRAs. On average, issuers employing reputable CRAs have a lower treasury spread when issuing new bonds. In addition, the investor protection environment and issuer's risk are two mechanisms through which the certification effect can benefit issuers. Specifically, the certification role of reputable CRAs are stronger for firms with worse investor protection environment and higher risk. Further, this thesis found that the certification effect was enhanced by the entry of CCR, which increased the rating information quality of existing issuer-pay CRAs in China, particularly for reputable CRAs. After CCR's entry, hiring reputable CRAs could save more treasury spread, which showed that the certification role of reputable CRAs was more valued by investors as their rating behaviour was disciplined by CCR. Moreover, for CCR-uncovered issuers, using reputable CRAs was associated with a greater spread saving. After CCR's entry, investors wanted to trust reputable CRAs when there was no rating by CCR, which verified the important role of CCR.

5.2 Contribution

- These findings complement the existing literature that documents a negative link between the entry of a new issuer-pay CRA and incumbent issuer-pay CRAs' rating inflation.
- These findings shed light on the debate concerning whether CRAs with alternative business models can alleviate the rating inflation problem.
- These findings supplement the existing literature that discusses how to improve the rating quality of issuer-pay CRAs.

- These findings supplement the existing literature on the certification effect of CRAs, particularly in the emerging market.
- These findings complement the debates on the reputational mechanism of CRAs.
- These findings generate policy implications regarding the distinct effects of different types of CRA on existing providers' rating strategies, and also emphasise the importance of investor protection environment construction.

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Appendices

Appendix 2.1: Market Share of Different Issuer-Pay Credit Rating Agencies

This table presents the market share of issuer-pay CRAs among different bond markets from 2006 to 2015. SCP is super commercial paper; CP is commercial paper; MTN is mid-term note; CB is corporate bond (supervised by NDRC); EB is enterprise bond (issued by listed firms and supervised by CSRC). Panel A reports the market share based on the bond issue number. Panel B reports the market share based on the bond issue volume.

Panel A: Market share based on issue number

	SCP	CP	MTN	CB	EB	Total
CCXI	43.98%	34.86%	35.17%	18.52%	0.00%	31.69%
Lianhe	24.95%	24.56%	26.46%	15.89%	0.00%	22.36%
Dagong	21.67%	22.75%	21.48%	20.34%	12.20%	21.35%
SBRC	8.70%	17.03%	16.46%	10.45%	9.16%	14.23%
Pengyuan	0.00%	0.00%	0.00%	30.79%	18.94%	6.10%
CCXR	0.00%	0.00%	0.00%	0.08%	32.14%	1.67%
UR	0.05%	0.00%	0.00%	0.23%	25.40%	1.35%
Golden	0.64%	0.36%	0.43%	3.55%	2.16%	1.04%
SFE	0.00%	0.45%	0.00%	0.15%	0.00%	0.20%

Panel B: Market share based on issue volume

	SCP	CP	MTN	CB	EB	Total
CCXI	44.51%	38.92%	36.07%	20.38%	0.00%	34.32%
Lianhe	27.14%	28.69%	36.84%	17.65%	0.00%	27.25%
Dagong	23.30%	21.29%	17.93%	26.72%	15.89%	21.36%
SBRC	4.53%	10.59%	8.91%	9.37%	8.00%	8.50%
Pengyuan	0.00%	0.00%	0.00%	22.78%	8.64%	4.02%
CCXR	0.00%	0.00%	0.00%	0.09%	39.94%	2.22%
UR	0.33%	0.00%	0.00%	0.24%	26.58%	1.58%
Golden	0.19%	0.17%	0.26%	2.64%	0.95%	0.63%
SFE	0.00%	0.33%	0.00%	0.14%	0.00%	0.12%

Appendix 2.2: Rating Classification

The ratings distribution in China is very different from developed markets. Although the ratings have 19 scales, ranging from C to AAA, most observations are concentrated in the ratings above A+. If we take ratings as a dependent variable and define each scale as a numerical number, we may mistakenly assume that the difference between each nearby rating is the same, and this may cause misleading results. Therefore, I use both practical and statistical rationales to reclassify the ratings.

Practical Background

To classify the ratings, I collected all ratings assigned by issuer-pay CRAs of all firms with a bond-issuing history between 2006 and 2015. From Appendix 2.2 Table 1, I can observe that 98.87% of 26,069 observations received ratings above A+.

Table 2.2.1: Rating Distribution of All Ratings from 2006 to 2015

Rating	N	Percentage (%)
AAA	4679	17.95
AAA–	5	0.02
AA+	5146	19.74
AA	10,658	40.88
AA–	4345	16.67
A+	941	3.61
A	163	0.63
A–	42	0.16
BBB+	15	0.06
BBB	12	0.05
BBB–	5	0.02
BB+	5	0.02
BB	14	0.05
BB–	3	0.01
B+	1	0
B	5	0.02
B–	2	0.01
CCC	6	0.02
CC	15	0.06
C	7	0.03
Total	26,069	100

Subsequently, I checked the ratings for firms who were rated in both the pre- and post-period (the regression sample). From Table 2.2.2, 98.81% of 17,516 observations are above A+.

Table 2.2.2: Rating Distribution for Firms in the Sample from 2006 to 2015

Rating	N	Percentage (%)
AAA	4153	23.71
AAA–	5	0.03
AA+	3857	22.02
AA	6211	35.46
AA–	2480	14.16
A+	601	3.43
A	119	0.68
A–	33	0.19
BBB+	7	0.04
BBB	5	0.03
BBB–	5	0.03
BB+	1	0.01
BB	11	0.06
BB–	2	0.01
B+	1	0.01
B	2	0.01
CCC	4	0.02
CC	14	0.08
C	5	0.03
Total	17,516	100

There are practical reasons behind this unbalanced distribution. First, some bond investors are restricted to buying bonds with certain ratings by industrial regulations. For example, according to the regulation issued by CSRC, money fund management companies can only invest in issuers with AAA ratings.[27] Further, based on the regulation by CIRC, insurance companies can only invest in issuers whose ratings are above A.[28] Second, to increase their leverage, bond investors refinance on the interbank and exchange markets through bond pledge repurchases; the bond conversion ratios are

[27] http://www.csrc.gov.cn/pub/newsite/flb/flfg/bmgf/jj/jjyz/201012/t20101231_189675.html
[28] http://www.csrc.gov.cn/pub/newsite/flb/flfg/bmgf/jj/jjyz/201012/t20101231_189675.html

mainly set by China Securities Depository and Clearing Corporation Limited (CSDC).[29] According to the official documents issued by CSDC, the lowest required pledge rating is AA. Third, issuers with certain ratings are encouraged and supported by government regulation. According to the NDRC, the bond issue procedure can be simplified to some extent for issuers whose ratings are above AA.[30] Last, underwriters have strong incentives to underwrite high-rating issuers in order to sell their bonds more easily. However, they also want to avoid the default risk in future, thus imposing internal restrictions on the issuers' ratings. For instance, some investment banks only underwrite issuers above AA,[31] and some specify that issuers for CPs must be above A+ and issuers for MTNs must be above AA–. Therefore, although there is no specific rating requirement from official supervisors, in practice, thresholds of ratings do exist in China.

Thus, bonds issued in China have their own special distributed ratings. Table 2.2.3 presents the issuers' rating for new issued bonds from 2006 to 2015. Among the total of 12,719 new bonds issued, only 76 issuers were below A+.

Table 2.2.3: Rating Distribution of New Bond Issuers from 2006 to 2015

Rating	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	Total
AAA	42	60	112	180	221	306	351	340	468	561	2641
AAA–	0	2	2	0	0	0	0	0	0	0	4
AA+	29	50	54	133	179	255	385	337	521	667	2610
AA	43	63	77	161	266	417	779	760	1117	1178	4861
AA–	50	76	84	146	159	254	425	331	304	216	2045
A+	36	69	47	39	24	58	95	67	31	16	482
A	13	23	7	4	8	5	1	1	0	0	62
A–	2	3	3	0	1	0	1	0	0	0	10
BBB+	0	0	2	0	1	0	0	0	0	0	3
BB+	0	0	0	0	0	0	0	0	1	0	1
Total	215	346	388	663	859	1295	2037	1836	2442	2638	12,719

In practice, I find there are several thresholds for issuers' ratings in China. The first is A+: issuers with A+ have a higher likelihood of issuing short-term CPs. The second is AA–: issuers can issue MTNs if their ratings are above AA–. The third cut-off point is

[29] There are still some bond pledge conversion ratios negotiated between financial institutions; however, in practice, bonds with ratings below AA are very hard to pledge. http://www.chinaclear.cn/zdjs/editor_file/20160708155313347.pdf.
[30] http://www.sdpc.gov.cn/zcfb/zcfbtz/201305/t20130522_542124.html
[31] https://wallstreetcn.com/articles/236341

AA because several regulatory documents use it to define high-quality issuers. The fourth is AAA (including AAA–).

Theoretical Background

CART analysis was used in the investigations. The goal of this method is to explore the best way to classify ratings into different categories in order to achieve the most accurate predictability. CART is a statistical method that explains the variation of a response variable using a set of explanatory variables or so-called predictors. The method is based on a recursive binary splitting of the data into mutually exclusive subgroups containing objects with similar properties. An important advantage of CART is that no assumption about the underlying distribution of the predictor variables is required, which is suitable for the ratings in China. The rationale for using CART is fourfold. First, the CART approach exhibits the capability of modelling complex relationship between variables without strong model assumptions. Second, CART can identify 'important' independent variables through the built tree and basic functions when many potential variables are considered. Third, CART does not need a long training process when the dataset is huge. Finally, one strong advantage of CART is that the resulting classification model can be easily interpreted. It not only points out which variables are important in classifying objects and observations, but also indicates that an observation belongs to a specific class when the built rules are satisfied. Given these advantages, CART has been proven to be an effective tool in handling forecasting and classification problems (Chai et al. 1996; Flagg, Giroux & Wiggins 1991; Griffin et al. 1997; Kuhnert, Do & Mcclure 2000; Lee et al. 2006; Ohmann et al. 1996).

Theory

CART was introduced by Breiman et al. (1984), using a parametric approach to pattern recognition. The methodology outlined in Breiman et al. (1984) can be summarised into three stages. The first stage involves growing the tree using a recursive partitioning technique to select variables and split points using a splitting criterion. Several criteria are available for determining the splits, including Gini, towing and ordered towing (for a more detailed description of the criteria, see Breiman et al. (1984)). After a large tree is identified, the second stage of the CART methodology uses a pruning procedure that incorporates a minimal cost complexity measure. The result of the pruning procedure is a nested subset of trees starting from the largest tree grown and continuing until only one node of the tree remains. Cross-validation or a testing sample is used to provide estimates of future classification errors for each subtree. Cross-validation is used when only small numbers of data points are available in building the CART models. The last stage of the methodology is to select the optimal tree that corresponds to a tree yielding the lowest cross-validated or testing set error rate. Trees in this stage have been identified as unstable. To avoid this instability, trees with smaller sizes, but comparable in accuracy (i.e., within one standard error), will be chosen as an alternative. This process is referred to as the one standard error rule and can be tuned to obtain trees of varying sizes and complexity. A measure of variable importance can be achieved by observing the drop in the error rate when another variable is used instead of the primary split. Basically, the more frequent a variable appears as a primary or surrogate split, the higher the importance score assigned (for more details regarding the model building process of CART, see Breiman et al. (1984) and Steinburg and Colla (1997)).

To verify the results, I further employed the method of random forests. Random forests or random decision forests (Ho 1995, 1998) are an ensemble learning method for classification, regression and other tasks that operate by constructing a multitude of decision trees at training time and outputting the class that is the mode of the classes (classification) or mean prediction (regression) of the individual trees. Random decision forests correct the decision trees' habit of overfitting their training set (Friedman, Hastie & Tibshirani 2001). Subsequently, I randomly divided the training and testing data 1,000 times to check the average predictability.

Empirical Results

There are 17,516 ratings in the dataset, which is the same as the sample I used in the DID analysis. All firms in the sample have been assigned ratings in both pre- and post-period. The ratings are given by existing issuer-pay CRAs in China, including initial ratings assigned when firms issued a new bond and the following ratings. Of the observations, 70% were randomly selected as the training sample (estimating the parameters of the corresponding built classification tree); the remaining 30% were used to test the model (comparing the predictability among different ways of classifying ratings). The dependent variable is the credit ratings of issuers—there are eight ways to classify different categories of ratings. The independent variables include tangibility; asset; ROA; leverage; sales growth; financial expense over income; current asset; cash equivalent; earnings before interest, tax, depreciation and amortisation (EBITDA) /

Interest; net operating cash; gross profit; short-term debt; industry dummy; and listing dummy. I tried two methods to investigate the tree. One method was to build a random tree, and the other method was to build a random forest through 1000 random splits to analyse the average classification accuracy.

From the results in Table 2.2.4, I compare the average correct classification rate (using training data) and the average correct prediction rate (using testing data). I find that the fifth and eighth ways have the highest correct classification and prediction rates. Consistent with the practical background, A+, AA–, AA and AAA are important thresholds in China's bond market. The detailed forecast accuracy for each rating category is also calculated.

Table 2.2.4: Prediction Accuracy of Different Classification Methods from the Classification and Regression Tree

		One random tree		Random forest 1000 times	
	Classification method	Classification accuracy	Prediction accuracy	Classification accuracy	Prediction accuracy
1	AAA = 19, CC = 1	77.64%	67.76%	96.02%	80.76%
2	AAA, AAA– = 9, AA+ = 8, AA = 7, AA– = 6, A+ = 5, A = 4, A– = 3, BBB+ = 2, others = 1	77.58%	67.73%	96.07%	80.84%
3	AAA, AAA– = 6, AA+ = 5, AA = 4, AA– = 3, A+ = 2, others = 1	79.60%	67.97%	96.15%	81.09%
4	AAA, AAA– = 5, AA+ = 4, AA = 3, AA– = 2, others = 1	79.38%	68.14%	96.21%	81.33%
5	AAA, AAA– = 5, AA+, AA = 4, AA– = 3, A+ = 2, others = 1	85.69%	78.33%	97.48%	86.19%
6	AAA, AAA– = 4, AA+ = 3, AA = 2, others = 1	81.62%	71.59%	96.47%	83.27%
7	AAA, AAA–, AA+ = 4, AA = 3, AA– = 2, others = 1	83.90%	73.40%	96.98%	83.50%
8	AAA, AAA– = 4, AA+, AA = 3, AA– = 2, others = 1	85.34%	78.74%	97.52%	86.58%

Therefore, from both a practical and theoretical perspective, it is necessary to reclassify the ratings in China in the following way: AAA, AAA– = 5; AA+, AA = 4; AA– = 3; A+ = 2; others = 1. This classification is consistent with the reality and has the highest prediction accuracy. I also present the prediction accuracy for each rating category in Table 2.2.5.

Table 2.2.5: Prediction Accuracy of the Classification and Regression Tree Using Testing Data

Panel A																			
Prediction	CC	CCC	B–	B	B+	BB–	BB	BB+	BBB–	BBB	BBB+	A–	A	A+	AA–	AA	AA+	AAA–	AAA	Predicted
CC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	Nil
CCC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	Nil
B–	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	Nil
B	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	Nil
B+	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	Nil
BB–	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	Nil
BB	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	Nil
BB+	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	Nil
BBB–	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	Nil
BBB	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	Nil
BBB+	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	Nil
A–	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	Nil
A	0	1	0	0	0	0	0	0	0	0	0	2	4	1	2	1	0	0	0	36.36%
A+	1	1	0	0	0	0	0	0	0	1	0	2	8	52	16	14	3	0	0	53.06%
AA–	2	1	0	0	0	0	3	0	0	0	0	2	16	82	322	173	37	0	1	50.39%
AA	0	3	0	1	0	1	2	0	0	1	0	4	7	52	382	1408	321	1	47	63.14%
AA+	0	0	0	0	0	0	0	0	0	0	0	0	0	4	28	194	716	0	101	68.65%
AAA–	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.00%
AAA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5	46	124	0	1059	85.82%

Panel B										
Prediction	Others	BBB +	A –	A	A +	AA–	AA	AA+	AAA, AAA–	Predicted accuracy
Others	0	0	0	0	0	0	0	0	0	Nil
BBB+	0	0	0	0	0	0	0	0	0	Nil
A–	0	0	0	0	0	0	0	0	0	Nil
A	1	0	2	4	1	2	1	0	0	36.36%
A+	3	0	2	8	52	16	14	3	0	53.06%
AA–	6	0	2	16	82	322	173	37	1	50.39%
AA	8	0	4	7	52	382	1408	321	48	63.14%
AA+	0	0	0	0	4	28	192	714	101	68.72%
AAA, AAA-	0	0	0	0	0	5	48	126	1059	85.54%

Panel C							
Prediction	Others	A+	AA–	AA	AA+	AAA, AAA–	Predicted accuracy
Others	19	3	19	6	0	0	40.43%
A+	10	54	23	12	3	0	52.94%
AA–	17	78	305	181	38	1	49.19%
AA	17	53	374	1393	305	46	63.67%
AA+	0	3	29	197	745	106	68.98%
AAA, AAA-	0	0	5	47	110	1056	86.70%

Panel D						
Prediction	Others	AA–	AA	AA+	AAA, AAA–	Predicted accuracy
Others	106	52	27	6	0	55.50%
AA–	75	303	167	35	4	51.88%
AA	69	352	1403	329	43	63.89%
AA+	4	43	192	714	107	67.36%
AAA, AAA-	0	5	47	117	1055	86.19%

Panel E						
Prediction	Others	A+	AA–	AA+, AA	AAA, AAA–	Predicted
Others	19	3	12	4	0	50.00%
A+	10	59	40	23	0	44.70%
AA–	19	58	298	191	2	52.46%
AA+, AA	15	71	404	2708	175	80.28%
AAA, AAA-	0	0	1	111	1032	90.21%

Panel F					
Prediction	Others	AA	AA+	AAA, AAA–	Predicted accuracy
Others	626	210	32	3	71.87%
AA	346	1361	332	45	65.31%
AA+	33	211	721	107	67.26%
AAA, AAA–	4	54	116	1054	85.83%

Panel G

Prediction	Other	AA−	AA	AAA, AAA−,	Predicted accuracy
Others	110	48	25	5	58.51%
AA−	80	336	177	35	53.50%
AA	60	332	1342	301	65.95%
AAA, AAA−,	4	39	292	2069	86.06%

Panel H

Prediction	Other	AA−	AA+, AA	AAA, AAA−	Predicted accuracy
Others	111	48	23	0	60.99%
AA−	73	293	181	2	53.37%
AA+, AA	70	411	2700	173	80.50%
AAA, AAA−	0	3	133	1034	88.38%

Appendix 2.3: Marginal Effects for the Ordinal Regression Model and the Ordinal Regression Model for Other Classifications

Panel A: Marginal effect for ORM

AAA, AAA– n = 4158	(3) Post = 0	N	(4) Post = 1	(4) – (3)	N	DID
(1) CCRcover = 0	0.137	197	0.216	0.079***	468	
(2) CCRcover = 1	0.219	1210	0.288	0.069***	2283	
(2) – (1)	0.082***		0.072***			–0.009
AA+, AA n = 10,068						
(1) CCRcover = 0	0.585	1190	0.605	0.020***	3460	
(2) CCRcover = 1	0.605	1744	0.587	–0.018***	3674	
(2–1)	0.020***		–0.018***			–0.039***
AA– n = 2480						
(1) CCRcover = 0	0.198	764	0.134	–0.064***	858	
(2) CCRcover = 1	0.132	508	0.096	–0.036***	350	
(2–1)	–0.066***		–0.038***			0.028***
A+ n = 601						
(1) CCRcover = 0	0.057	243	0.033	–0.024***	183	
(2) CCRcover = 1	0.032	128	0.021	–0.011***	47	
(2–1)	–0.025***		–0.012***			0.014***
Others n = 209						
(1) CCRcover = 0	0.023	83	0.012	–0.011***	76	
(2) CCRcover = 1	0.012	30	0.008	–0.004***	20	
(2–1)	–0.011***		–0.004***			0.006***

Panel B: ORM for other rating classifications

	(1)	(2)	(3)	(4)
	AAA, AAA– = 9, AA+ = 8, AA = 7, AA– = 6, A+ = 5, A = 4, A– = 3, BBB+ = 2, others = 1	AAA, AAA– = 6, AA+ = 5, AA = 4, AA– = 3, A+ = 2, others = 1	AAA, AAA– = 5, AA + =4, AA = 3, AA– = 2, others = 1	AAA, AAA–= 4, AA+, AA = 3, AA– = 2, others = 1
CCRcover*Post	–0.178***	–0.180***	–0.183***	–0.232***
	(0.062)	(0.062)	(0.062)	(0.068)
CCRcover	0.767***	0.768***	0.767***	0.747***
	(0.054)	(0.054)	(0.054)	(0.059)
Post	0.594***	0.596***	0.598***	0.722***
	(0.048)	(0.048)	(0.048)	(0.052)
Sales	0.858***	0.858***	0.859***	0.871***
	(0.013)	(0.013)	(0.013)	(0.014)
Leverage	–0.035***	–0.035***	–0.034***	–0.038***
	(0.001)	(0.001)	(0.001)	(0.001)
ROA	–0.297***	–0.299***	–0.305***	–0.309***
	(0.037)	(0.037)	(0.036)	(0.040)
Tangibility	0.758***	0.759***	0.763***	0.646***
	(0.076)	(0.076)	(0.076)	(0.084)
Growth	0.003***	0.003***	0.003***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
Cash equivalent	0.241***	0.242***	0.244***	0.194***
	(0.031)	(0.031)	(0.031)	(0.029)
Observations	17,388	17,388	17,388	17,388
Pseudo R-squared	0.174	0.176	0.179	0.210

Appendix 2.4: Ordinary Least Squares Results of Different Classifications Using an Unmatched Full Sample

	(1)	(2)	(3)	(4)
	AAA, AAA– = 9, AA+ = 8, AA = 7, AA– = 6, A+ = 5, A = 4, A– = 3, BBB+ = 2, others = 1	AAA, AAA– = 6, AA+ = 5, AA = 4, AA– = 3, A+ = 2, others = 1	AAA, AAA– = 5, AA+ = 4, AA = 3, AA– = 2, others = 1	AAA, AAA– = 4, AA+, AA = 3, AA– = 2, others = 1
CCRcover*Post	–0.051*	–0.060**	–0.051**	–0.088***
	(0.028)	(0.026)	(0.026)	(0.018)
CCRcover	0.380***	0.376***	0.359***	0.242***
	(0.024)	(0.023)	(0.022)	(0.015)
Sales	0.430***	0.419***	0.411***	0.256***
	(0.005)	(0.004)	(0.004)	(0.003)
Leverage	–0.015***	–0.014***	–0.013***	–0.009***
	(0.000)	(0.000)	(0.000)	(0.000)
ROA	0.013**	0.004	0.001	0.000
	(0.005)	(0.005)	(0.005)	(0.003)
Tangibility	0.030	0.057	0.066*	0.021
	(0.041)	(0.039)	(0.038)	(0.027)
Growth	0.001	0.001	0.001	0.001**
	(0.001)	(0.000)	(0.000)	(0.000)
Cash equivalent	0.053***	0.053***	0.052***	0.031***
	(0.007)	(0.006)	(0.006)	(0.004)
Constant	5.765***	2.713***	1.796***	1.883***
	(0.092)	(0.087)	(0.085)	(0.059)
Observations	17,388	17,388	17,388	17,388
R-squared	0.500	0.517	0.521	0.462
Industry fixed effects	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes

Appendix 2.5: Difference-In-Differences Analysis of Ratings for a Particular Time Period

Columns 1 to 4 present the DID analysis results excluding samples in 2012 using the PSM sample. Column 5 presents the results of the PSM sample if the post-period is changed to 2011.

	(1) Baseline results	(2) Reputation		(3) Investor protection		(4) Rating frequency		(5) Post = year after 2011
	PSM	Non-reputable	Reputable	Low IPI	High IPI	Low frequency	High frequency	PSM sample
CCRcover*Post	–0.056**	0.032	–0.128***	0.013	–0.120***	0.025	–0.092**	–0.035
	(0.024)	(0.039)	(0.036)	(0.036)	(0.037)	(0.033)	(0.046)	(0.021)
Diff. of coefficient		–0.160 ***	Chi2 = 9.24	–0.133**	(chi = 6.63)	–0.117**	(chi = 4.24)	
CCRcover	0.194***	0.123***	0.240***	0.152***	0.237***	0.093***	0.111***	0.174***
	(0.018)	(0.034)	(0.028)	(0.030)	(0.032)	(0.028)	(0.036)	(0.015)
Sales	0.283***	0.269***	0.292***	0.286***	0.268***	0.318***	0.233***	0.283***
	(0.004)	(0.007)	(0.006)	(0.008)	(0.006)	(0.006)	(0.006)	(0.003)
Leverage	–0.010***	–0.011***	–0.010***	–0.014***	–0.007***	–0.014***	–0.007***	–0.010***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
ROA	0.003	–0.104***	0.007***	0.000	0.003*	0.005**	–0.015	0.002
	(0.004)	(0.030)	(0.001)	(0.027)	(0.002)	(0.002)	(0.036)	(0.004)
Tangibility	0.040	0.120**	0.007	0.041	0.150***	0.054	–0.088*	0.051*
	(0.032)	(0.053)	(0.043)	(0.044)	(0.052)	(0.046)	(0.048)	(0.029)
Growth	0.006	0.000	0.027***	0.001	0.050***	0.005	0.004	0.003
	(0.004)	(0.004)	(0.008)	(0.003)	(0.014)	(0.005)	(0.011)	(0.003)
Cash equivalent	0.062***	0.040***	0.123***	0.051***	0.134***	0.051***	0.137***	0.068***
	(0.008)	(0.012)	(0.026)	(0.016)	(0.052)	(0.013)	(0.025)	(0.008)
Constant	2.794***	2.490***	2.835***	2.703***	2.792***	2.620***	3.094***	2.797***
	(0.065)	(0.229)	(0.106)	(0.158)	(0.132)	(0.163)	(0.131)	(0.063)
Observations	11,433	4676	6757	5807	5626	6077	5356	13,511
R-squared (adjusted)	0.471	0.436	0.495	0.434	0.489	0.453	0.438	0.471
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Appendix 2.6: Difference-In-Differences Analysis of Rating Categorised by the Reputation of Issuer-Pay Credit Rating Agencies and Investor protection environment for the Propensity Score Matching Sample

	(1)		(2)		(3)	
	Non-reputable	Reputable	Low IPI	High IPI	Low frequency	High frequency
CCRcover*Post	0.032	–0.135***	0.002	–0.118***	0.019	–0.113**
	(0.038)	(0.034)	(0.034)	(0.036)	(0.032)	(0.044)
Diff. of coefficient	–0.143***	chi2 = 10.65	–0.111**	chi2 = 5.84	–0.127**	chi2 = 5.84
CCRcover	0.124***	0.242***	0.152***	0.239***	0.091***	0.116***
	(0.034)	(0.028)	(0.030)	(0.031)	(0.028)	(0.036)
Sales	0.270***	0.291***	0.288***	0.268***	0.320***	0.229***
	(0.006)	(0.005)	(0.007)	(0.005)	(0.006)	(0.005)
Leverage	–0.011***	–0.010***	–0.014***	–0.006***	–0.014***	–0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ROA	–0.084***	0.006***	–0.012	0.003	0.004	–0.014
	(0.028)	(0.001)	(0.024)	(0.002)	(0.002)	(0.032)
Tangibility	0.147***	0.007	0.058	0.155***	0.045	–0.059
	(0.048)	(0.040)	(0.040)	(0.048)	(0.042)	(0.043)
Growth	–0.000	0.028***	0.000	0.052***	0.003	0.002
	(0.002)	(0.008)	(0.002)	(0.014)	(0.002)	(0.010)
Cash equivalent	0.043***	0.132***	0.055***	0.144***	0.059***	0.127***
	(0.014)	(0.023)	(0.018)	(0.047)	(0.016)	(0.024)
Constant	2.460***	2.813***	2.691***	2.782***	2.627***	3.057***
	(0.228)	(0.104)	(0.157)	(0.130)	(0.164)	(0.127)
Observations	5658	7853	6887	6624	7271	6240
R-squared (adjusted)	0.496	0.496	0.424	0.494	0.444	0.441
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes

Appendix 2.7: Difference-In-Differences Analysis of Ratings Categorised by the Reputation of Issuer-Pay Credit Rating Agencies and Investor protection environment for the Heckman Sample

	(1)		(2)		(3)	
	Non-reputable	Reputable	Low IPI	High IPI	Low frequency	High frequency
CCRcover*Post	–0.008	–0.170***	–0.055*	–0.150***	–0.017	–0.124***
	(0.031)	(0.030)	(0.029)	(0.030)	(0.031)	(0.033)
Diff. of coefficient	–0.162***	chi2 = 14.23	–0.095**	chi2 = 5.17	–0.107**	chi2 = 5.47
CCRcover	0.187***	0.309***	0.250***	0.265***	0.153***	0.151***
	(0.029)	(0.026)	(0.026)	(0.028)	(0.029)	(0.029)
Sales	0.224***	0.236***	0.384***	0.170***	0.253***	0.221***
	(0.016)	(0.013)	(0.021)	(0.012)	(0.021)	(0.013)
Leverage	–0.009***	–0.011***	–0.007***	–0.010***	–0.014***	–0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ROA	–0.007	–0.000	0.134***	–0.006	–0.016	0.004***
	(0.028)	(0.003)	(0.028)	(0.005)	(0.026)	(0.001)
Tangibility	0.036	–0.187***	0.465***	–0.231***	–0.131	0.021
	(0.071)	(0.059)	(0.075)	(0.061)	(0.081)	(0.062)
Growth	0.002	0.011***	–0.017***	0.011*	0.006**	–0.019*
	(0.003)	(0.003)	(0.003)	(0.006)	(0.003)	(0.010)
Cash equivalent	0.049***	0.026*	0.027**	0.107***	0.026**	0.158***
	(0.016)	(0.015)	(0.011)	(0.031)	(0.013)	(0.022)
Inverse Mill ratio	–0.091	–0.247***	0.704***	–0.548***	–0.143	–0.050
	(0.090)	(0.081)	(0.108)	(0.075)	(0.108)	(0.091)
Constant	2.445***	3.399***	1.171***	3.820***	3.080***	2.872***
	(0.270)	(0.175)	(0.262)	(0.183)	(0.284)	(0.199)
Observations	8263	9118	8622	8759	9298	8083
R-squared (adjusted)	0.398	0.496	0.386	0.498	0.359	0.459
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes

Appendix 2.8: Rating Inflation Change and Additional Check on Conditional Regression

	Rating (full sample)			
	Investor protection index		Rating frequency	
	Non-reputable	Reputable	Non-reputable	Reputable
CCRcover*Post	–0.014	–0.241***	0.059	–0.245***
	(0.045)	(0.044)	(0.049)	(0.043)
Diff. of coefficient (Reputable – Non-reputable)	–0.227***	(chi = 13.20)	–0.304***	(chi = 21.58)
CCRcover	0.141***	0.397***	-0.048	0.288***
	(0.043)	(0.037)	(0.045)	(0.035)
Sales	0.266***	0.260***	0.203***	0.243***
	(0.008)	(0.006)	(0.007)	(0.006)
Leverage	–0.009***	–0.006***	–0.002**	–0.007***
	(0.001)	(0.001)	(0.001)	(0.001)
ROA	0.040	0.002	–0.092***	0.007***
	(0.033)	(0.002)	(0.031)	(0.001)
Tangibility	0.021	0.079	0.326***	–0.076
	(0.072)	(0.060)	(0.060)	(0.049)
Growth	0.000	0.001***	–0.001***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Cash equivalent	0.086*	0.157***	0.131***	0.171***
	(0.048)	(0.029)	(0.036)	(0.025)
Constant	2.221***	2.826***	2.272***	2.892***
	(0.365)	(0.110)	(0.291)	(0.115)
Observations	4025	4737	3014	5072
R-squared (adjusted)	0.446	0.519	0.455	0.481
Industry fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes

Appendix 2.9: An Alternative Measurement for the Investor protection environment—Marketization Index

	Raw Sample (1)		Heckman Sample (2)		PSM Sample (3)	
	Low MI	High MI	Low MI	High MI	Low MI	High MI
CCRcover*Post	–0.024	–0.162***	–0.059**	–0.160***	–0.010	–0.096***
	(0.029)	(0.030)	(0.030)	(0.031)	(0.035)	(0.035)
Diff. of coefficient						
(High – Low MI)	–0.138***	chi2 = 10.85	–0.266**	chi2 = 5.52	–0.333*	chi2 = 2.94
CCRcover	0.216***	0.305***	0.240***	0.291***	0.161***	0.210***
	(0.026)	(0.028)	(0.028)	(0.028)	(0.030)	(0.031)
Leverage	0.241***	0.263***	0.398***	0.293***	0.284***	0.268***
	(0.007)	(0.005)	(0.075)	(0.008)	(0.007)	(0.005)
ROA	–0.010***	–0.008***	–0.008***	–0.008***	–0.013***	–0.006***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Tangibility	0.014	0.004*	0.100*	0.004**	–0.004	0.003
	(0.023)	(0.002)	(0.053)	(0.002)	(0.024)	(0.002)
Sales (log)	0.057	0.062	0.206***	0.152***	0.070*	0.159***
	(0.038)	(0.047)	(0.071)	(0.047)	(0.040)	(0.047)
Growth	0.001*	0.001***	–0.016	–0.007	–0.001	0.046***
	(0.000)	(0.000)	(0.010)	(0.011)	(0.001)	(0.010)
Cash equivalent	0.023**	0.136***	0.025**	0.190***	0.049***	0.159***
	(0.011)	(0.036)	(0.011)	(0.024)	(0.014)	(0.048)
Inverse Mill ratio			0.673*	0.025		
			(0.359)	(0.035)		
Constant	2.580***	2.808***	1.618***	2.704***	2.660***	2.736***
	(0.149)	(0.124)	(0.523)	(0.127)	(0.163)	(0.130)
Observations	8793	8595	8314	8055	6599	6912
R-squared	0.380	0.493	0.409	0.512	0.425	0.498
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes

Appendix 3.1: Information Content of Rating Changes of Issuer-Pay Rating Agencies for Downgrades for a Particular Time Period

This table presents the 21-trading-day CARs (in percentage) for bonds surrounding the downgrades rating change announcements of incumbent issuer-pay CRAs. The sample consists of issuer-pay CRAs' rating downgrades announcements for firms that CCR initiated coverage of between 2012 and the end of 2015. Rating changes are from 2006 to 2011 and 2013 to 2015. Column 1 shows the results for the baseline model, applying the normal sample and IV sample respectively. Column 2 presents the regression results conditional on CRAs' reputations. Columns 3 and 4 present regression results conditional on the investor protection environment of issuers, measured by IPI and rating frequency respectively. All variables are the same as Table 3.2. Industry fixed effects are indicator variables for firms' industry. Standard errors are in parentheses. R-squared is reported. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels respectively.

	(1) Baseline results		(2) Reputation		(3) Investor protection		(4) Rating frequency	
	Base model	IV	Non-reputable	Reputable	Low IPI	High IPI	Low frequency	High frequency
CCRfirstcover	–4.505**		–0.424*	–8.385***	0.018	–7.436***	–0.028	–4.876**
	(1.755)		(0.225)	(3.107)	(0.252)	(2.868)	(0.242)	(2.215)
CCRfirstcover (instrumented)		–3.364**						
		(1.584)						
Diff. of coefficient			–7.961**	Chi2 = 6.53	–7.454***	Chi2 = 6.70	–4.848**	Chi2 = 4.73
Sales	–0.272	–0.704	0.156	–0.062	0.001	–1.205	0.003	–0.457
	(0.814)	(0.801)	(0.130)	(1.018)	(0.103)	(1.197)	(0.182)	(1.189)
Leverage	0.283***	0.292***	–0.037**	0.683***	0.016	0.668***	–0.020	0.682***

	(0.092)	(0.093)	(0.015)	(0.236)	(0.013)	(0.210)	(0.014)	(0.211)
ROA	0.121	0.175	–0.046*	0.109	0.003	0.419	–0.030	0.101
	(0.240)	(0.239)	(0.025)	(0.350)	(0.033)	(0.280)	(0.034)	(0.398)
Tangibility	–6.847	–8.302*	0.209	–7.475	–0.744	–25.505**	–0.628	–3.645
	(4.281)	(4.316)	(0.471)	(5.084)	(0.745)	(10.230)	(0.800)	(4.418)
Growth	–0.180	0.386	0.730***	-0.594	0.380	–1.493**	0.758***	0.505
	(1.002)	(0.981)	(0.188)	(0.930)	(0.262)	(0.750)	(0.163)	(0.770)
Cash equivalent	8.656***	8.792***	–0.190	16.491**	0.953**	9.634***	–0.130	32.499***
	(2.620)	(2.641)	(0.554)	(7.787)	(0.400)	(3.269)	(0.315)	(11.490)
Constant	–15.368**	–15.540**	2.005**	–45.699**	–1.573**	–28.898***	1.419	–50.827***
	(6.529)	(6.567)	(0.970)	(18.250)	(0.789)	(10.060)	(0.941)	(15.940)
Observations	227	227	122	105	240	117	94	133
R-squared	0.164	0.156	0.141	0.313	0.149	0.359	0.373	0.373
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Appendix 3.2: Information Content of Rating Changes of Issuer-Pay Rating Agencies for Downgrades—11-Day Event Window, 60-Trading-Day Estimation Window

	(1) 11-day event window	(2) 60-trading-day estimation window
CCRfirstcover	–2.591**	–3.582***
	(1.237)	(1.317)
Sales	0.131	–0.320
	(0.605)	(0.626)
Leverage	0.084	0.219***
	(0.068)	(0.072)
ROA	0.099	0.156
	(0.177)	(0.188)
Tangibility	–2.317	–5.120
	(3.242)	(3.413)
Growth	0.246	0.143
	(0.772)	(0.865)
Cash equivalent	4.766**	7.427***
	(2.021)	(2.173)
Constant	–5.595	–12.000**
	(4.932)	(5.289)
Observations	255	293
R-squared	0.078	0.133
Industry fixed effects	Yes	Yes

Appendix 3.3: Alternative Instrumental Variable Regression for Downgrades

This table presents the results of the IV regressions, applied another way to calculate the IV. The sample consists of issuer-pay CRAs' rating downgrade announcements for firms that CCR initiated coverage of between 2012 and the end of 2015. Rating changes are between 2006 and 2015. The first stage is the logit regression of CCRfirstcover dummy on Ind–Mean–Asset. CCRfirstcover is a dummy variable equal to one if the event date of rating change is during the post-coverage date, zero otherwise. Ind–Mean–Asset is the industry average total asset (measured as the logarithm of total asset) of each firm's industry in the prior year, calculated using only CCR-covered firms as of 2015. Also included in the first-stage regression in Column 1 are the same control variables as those in the corresponding second stage and for the exclusion restriction test. Industries are classified by codes defined by CSRC. The first day of issuer-year with the highest predicted probability of CCR's coverage initiation for each issuer is assigned as the instrumented date for CCR's coverage initiation. The instrumented CCRfirstcover equals one if the event date of rating changes is after the instrumented date for CCR's coverage initiation, zero otherwise. Column 2 shows the results for the second-stage regression. All variables are the same as Table 3.2. Industry fixed effects are indicator variables for firms' industry. Standard errors are in parentheses. R-squared is reported. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels respectively.

	(1) First stage	(2) Second stage	
CCRfirstcover (instrumented)		–3.143**	-3.156**
		(1.353)	(1.358)
Ind–Mean–Asset	8.599***		
	(1.352)		
Sales	0.293	–0.793	–0.620
	(0.203)	(0.620)	(0.701)
Leverage	0.029	0.238***	0.270***
	(0.022)	(0.078)	(0.080)
ROA	–0.000	0.186	0.204
	(0.057)	(0.202)	(0.208)
Tangibility	1.591	–5.380*	–7.676**
	(1.048)	(3.242)	(3.790)
Growth	–0.516	0.733	0.494
	(0.555)	(0.885)	(0.901)
Cash equivalent	0.938	7.468***	8.631***
	(0.654)	(2.314)	(2.393)
Constant	–61.912***	–13.478**	–14.854**
	(9.823)	(5.408)	(5.800)
Observations	257	262	262
LR Chi-squared	125.60		
Prob (Chi-squared)	0.000		
(Pseudo) R-squared	0.369	0.087	0.144
Industry fixed effects	Yes	No	Ye

Appendix 3.4: An Alternative Measurement for the Investor protection environment

This table presents the results of 21-trading-day CARs surrounding rating downgrades, conditional on MI. The left-hand-side variable is the 21-day CARs surrounding rating change announcements. CCRfirstcover is a dummy variable equal to one if the event date of rating change is during the post-coverage date, otherwise zero. The high MI group consists of issuers who come from the provinces with an MI above the sample median; otherwise the issuer belongs to the low MI group. All variables are the same as Table 3.2. Industry fixed effects are indicator variables for firms' industry. Standard errors are in parentheses. R-squared is reported. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels respectively.

Devp. Var = CARs		
	Low MI	High MI
CCRfirstcover	-0.167	–6.011***
	(0.232)	(2.225)
Diff. of coefficient (High – Low MI)	–5.844***	(chi = 6.82)
Sales	0.031	–1.035
	(0.116)	(1.052)
Leverage	0.016	0.642***
	(0.011)	(0.206)
ROA	0.062	0.847**
	(0.049)	(0.349)
Tangibility	–1.046	–21.866**
	(0.734)	(8.681)
Growth	–0.010	–0.497
	(0.447)	(0.695)
Cash equivalent	0.740*	12.185***
	(0.385)	(4.480)
Constant	–1.437**	–33.076***
	(0.707)	(11.266)
Observations	132	130
R-squared (adjusted)	0.128	0.331
Industry fixed effects	Yes	Yes
Year fixed effects	No	No

Appendix 3.5: Event Study Using the Classification as Follows—AAA, AAA– = 9; AA+ = 8; AA = 7; AA– = 6; A+ = 5; A = 4; A– = 3; BBB+ = 2; others = 1

This table presents the results of 21-trading-day CARs surrounding rating downgrades; the rating change events are defined using a new rating classification. The left-hand-side variable is the 21-day CARs surrounding rating change announcements. CCRfirstcover is a dummy variable equal to one if the event date of rating change is during the post-coverage date, otherwise zero. All variables are the same as Table 3.2. Industry fixed effects are indicator variables for firms' industry. Standard errors are in parentheses. R-squared is reported. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels respectively.

	(1) Baseline results	
	Base model	IV
CCRfirstcover	–3.426***	
	(0.855)	
CCRfirstcover (instrumented)		–2.615***
		(0.822)
Sales	–0.947*	–1.237**
	(0.511)	(0.513)
Leverage	0.265***	0.261***
	(0.046)	(0.046)
ROA	0.277**	0.304**
	(0.121)	(0.122)
Tangibility	–1.287	–0.980
	(2.298)	(2.307)
Growth	–0.488	–0.046
	(0.718)	(0.711)
Cash equivalent	8.472***	8.037***
	(1.512)	(1.517)
Constant	–14.333***	–13.876***
	(3.400)	(3.464)
Observations	548	548
R-squared	0.152	0.143
Industry fixed effects	Yes	Yes

Appendix 4.1: Bond Issuance Yield and Reputation of Credit Rating Agencies Using Different Rating Scales Respectively

This table presents the relationship between the bond issuance yield and reputation of CRAs for each rating scale from 1 to 5. The left-hand variable is treasury spread, which is the difference between the issue's offering yield and the yield on a benchmark treasury security. All the variables are the same as those in Table 4.2. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels respectively.

	(1)	(2)	(3)	(4)	(5)
	A	A+	AA–	AA, AA+	AAA–, AAA
Reputation	0.292	–0.267***	–0.135***	–0.158***	–0.005
	(0.240)	(0.081)	(0.040)	(0.018)	(0.022)
Maturity	–0.035	0.044	0.126***	0.090***	0.012***
	(0.056)	(0.034)	(0.015)	(0.004)	(0.003)
Volume	–0.099	0.062	0.178***	0.016	–0.001
	(0.188)	(0.079)	(0.041)	(0.015)	(0.014)
Enhancement	–0.696**	–1.023***	–0.620***	–0.196***	–0.270***
	(0.276)	(0.171)	(0.081)	(0.031)	(0.063)
Sales	0.015	–0.095*	–0.034	–0.066***	–0.067***
	(0.148)	(0.052)	(0.022)	(0.009)	(0.008)
Leverage	–0.008	0.000	0.001	0.001	0.009***
	(0.008)	(0.004)	(0.002)	(0.001)	(0.001)
Tangibility	–0.900	–0.256	–0.349***	–0.170***	0.077
	(0.563)	(0.276)	(0.127)	(0.055)	(0.059)
ROA	0.018	–0.004	0.006	0.001	–0.000
	(0.021)	(0.009)	(0.005)	(0.002)	(0.000)
Growth	0.061	0.009	0.002	0.001	–0.014
	(0.115)	(0.015)	(0.002)	(0.001)	(0.011)
Cash equivalent	–0.592	0.019	0.000	–0.009**	0.027
	(0.649)	(0.116)	(0.013)	(0.004)	(0.027)
Constant	2.722***	2.221***	1.468***	1.349***	1.098***
	(0.756)	(0.375)	(0.189)	(0.108)	(0.104)
Observations	72	469	1,959	6837	2397
R-squared	0.777	0.610	0.447	0.310	0.307
Industry and year fixed effects	Yes	Yes	Yes	Yes	Yes

Appendix 4.2: Bond Issuance Yield and Reputation of Credit Rating Agencies for Each Issuance Year

This table presents the relationship between the bond issuance yield and reputation of CRAs for each year between 2006 and 2015. The left-hand variable is the treasury spread, which is the difference between the issue's offering yield and the yield on a benchmark treasury security. All the variables are the same as those in Table 4.2. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
Reputation	–0.026	0.014	–0.120*	–0.126***	–0.060*	–0.141**	–0.088***	–0.084***	–0.194***	–0.121***
	(0.039)	(0.057)	(0.063)	(0.047)	(0.032)	(0.055)	(0.030)	(0.028)	(0.034)	(0.033)
Maturity	–0.030***	–0.010	–0.011	0.074***	0.057***	0.038***	0.115***	0.077***	0.075***	0.079***
	(0.009)	(0.016)	(0.015)	(0.011)	(0.007)	(0.013)	(0.007)	(0.006)	(0.007)	(0.008)
Volume	–0.150***	–0.172***	–0.027	0.060	0.038	–0.042	0.106***	0.052**	0.037	–0.001
	(0.035)	(0.049)	(0.049)	(0.038)	(0.026)	(0.043)	(0.026)	(0.022)	(0.026)	(0.026)
Issuer's rating	–0.110***	–0.274***	–0.555***	–0.530***	–0.214***	–0.506***	–0.811***	–0.626***	–1.008***	–1.135***
	(0.022)	(0.032)	(0.041)	(0.040)	(0.029)	(0.050)	(0.029)	(0.028)	(0.038)	(0.040)
Enhancement	–0.363***	–0.536***	0.046	0.209**	0.049	–0.401***	–0.236***	–0.126**	–0.281***	–0.305***
	(0.119)	(0.171)	(0.124)	(0.083)	(0.049)	(0.098)	(0.049)	(0.050)	(0.060)	(0.071)
Sales	0.015	0.048**	–0.018	–0.098***	–0.113***	–0.107***	–0.146***	–0.080***	–0.004	0.016
	(0.021)	(0.024)	(0.025)	(0.019)	(0.012)	(0.025)	(0.014)	(0.013)	(0.016)	(0.015)
Leverage	–0.000	–0.001	0.005*	–0.000	–0.000	–0.000	0.000	0.002**	0.000	0.005***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Tangibility	0.154	–0.434***	–0.053	–0.148	–0.243***	–0.114	–0.191**	–0.204**	–0.262**	–0.136
	(0.115)	(0.155)	(0.163)	(0.141)	(0.091)	(0.161)	(0.094)	(0.082)	(0.104)	(0.104)
ROA	0.009*	0.003	–0.001	0.003	–0.005	–0.009	–0.003	0.008**	0.000	0.015***
	(0.005)	(0.006)	(0.007)	(0.005)	(0.004)	(0.007)	(0.003)	(0.003)	(0.001)	(0.005)

Growth	0.068	–0.032	0.008	0.012	0.002***	0.001	0.024	0.000	–0.006	–0.037***
	(0.070)	(0.037)	(0.049)	(0.013)	(0.001)	(0.002)	(0.015)	(0.003)	(0.010)	(0.014)
Cash equivalent	–0.018	0.022	0.210**	0.025	–0.018***	0.109**	–0.031**	–0.012	–0.003	0.006
	(0.072)	(0.051)	(0.084)	(0.042)	(0.004)	(0.047)	(0.012)	(0.009)	(0.006)	(0.031)
Constant	2.211***	3.106***	4.286***	4.004***	2.603***	5.254***	5.852***	4.627***	6.388***	6.084***
	(0.148)	(0.184)	(0.220)	(0.202)	(0.129)	(0.228)	(0.124)	(0.121)	(0.155)	(0.171)
Observations	205	335	363	601	824	1197	1848	1728	2344	2289
R-squared	0.729	0.579	0.688	0.666	0.557	0.327	0.643	0.526	0.441	0.436
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Appendix 4.3: Bond Issuance Yield and Reputation of Credit Rating Agencies for Different Maturity Categories

This table presents the relationship between the bond issuance yield and reputation of CRAs for different maturity ranges. The left-hand variable is the treasury spread, which is the difference between the issue's offering yield and the yield on a benchmark treasury security. All the variables are the same as those in Table 4.2. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels respectively.

	(1)	(2)	(3)
	Maturity < 3 years	3 years <= Maturity <= 5 years	Maturity > 5 years
Reputation	–0.147***	–0.104***	–0.348***
	(0.023)	(0.025)	(0.035)
Volume	–0.181***	–0.038**	–0.039
	(0.018)	(0.018)	(0.034)
Issuer's rating	–0.500***	–0.771***	–0.655***
	(0.018)	(0.029)	(0.038)
Enhancement	–0.438***	–0.540***	–0.374***
	(0.082)	(0.052)	(0.038)
Sales	0.025**	–0.057***	–0.073***
	(0.012)	(0.011)	(0.014)
Leverage	0.004***	0.006***	–0.003**
	(0.001)	(0.001)	(0.001)
Tangibility	–0.438***	0.074	–0.724***
	(0.067)	(0.076)	(0.110)
ROA	0.008***	0.000	–0.005
	(0.003)	(0.001)	(0.006)
Growth	–0.003	0.009	0.001
	(0.020)	(0.008)	(0.001)
Cash equivalent	0.019	0.007	–0.009**
	(0.033)	(0.023)	(0.004)
Constant	4.257***	5.521***	6.045***
	(0.096)	(0.126)	(0.172)
Observations	5884	3356	2494
R-squared	0.334	0.376	0.425
Industry and year fixed effects	Yes	Yes	Yes

Appendix 4.4: Bond Issuance Yield and Reputation of Credit Rating Agencies for Different Categories of Bonds

This table presents the relationship between the bond issuance yield and the reputation of CRAs for each type of bond. The left-hand variable is the treasury spread, which is the difference between the issue's offering yield and the yield on a benchmark treasury security. All the variables are the same as those in Table 4.2. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels respectively.

	(1)	(2)	(3)
	CP	MTN	CB
Reputation	–0.115***	–0.091***	–0.160***
	(0.020)	(0.023)	(0.031)
Maturity	0.144	–0.001	–0.035***
	(0.124)	(0.007)	(0.009)
Volume	–0.060***	–0.012	–0.078**
	(0.017)	(0.017)	(0.033)
Issuer's rating	–0.653***	–0.781***	–0.522***
	(0.018)	(0.028)	(0.034)
Enhancement	–0.568***	–0.553***	–0.116***
	(0.073)	(0.056)	(0.034)
Sales	0.026**	–0.054***	–0.086***
	(0.011)	(0.010)	(0.012)
Leverage	0.002**	0.006***	–0.002**
	(0.001)	(0.001)	(0.001)
Tangibility	–0.173***	0.103	–0.155
	(0.060)	(0.068)	(0.108)
ROA	0.006**	–0.000	–0.004
	(0.002)	(0.001)	(0.005)
Growth	–0.027	–0.000	0.001
	(0.018)	(0.008)	(0.001)
Cash equivalent	0.011	–0.011	–0.006*
	(0.029)	(0.026)	(0.004)
Constant	3.683***	5.647***	4.310***
	(0.154)	(0.158)	(0.233)
Observations	5851	3515	2368
R-squared	0.476	0.456	0.578
Industry and year fixed effects	Yes	Yes	Yes

Appendix 4.5: Certification Effect Comparison between China Credit Rating-Covered and China Credit Rating-Uncovered Issuers Using Propensity Score Matching Sample

This table presents the certification effect change before and after CCR's entry. The sample consists of 7817 issuance observations for 1327 issuers from 2012 to the end of 2015. There are 814 firms covered by CCR and 513 firms are 1-to-1 matched from the CCR-uncovered group. Columns 1 to 4 present the results for Eq. 4.10 using the PSM sample. The left-hand variable is the treasury spread. All the variables are the same as those in Table 4.5. The Heckman sample shows results when considering the sample selection bias of choosing reputable CRAs. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels respectively.

	PSM sample				Heckman PSM sample	
	(1)	(2)	(3)	(4)	First stage (5)	Second stage (6)
Reputation*CCRcover	0.215***	0.097**	0.209***	0.102**		0.104**
	(0.059)	(0.049)	(0.055)	(0.049)		(0.049)
Reputation	–0.389***	–0.159***	–0.340***	–0.167***		0.105
	(0.053)	(0.044)	(0.049)	(0.044)		(0.239)
CCRcover	–0.474***	–0.121***	–0.369***	–0.125***		–0.132***
	(0.043)	(0.037)	(0.040)	(0.036)		(0.037)
Maturity		0.063***		0.064***	–0.037***	0.068***
		(0.004)		(0.004)	(0.008)	(0.005)
Volume		–0.004		0.023	0.064**	0.016
		(0.014)		(0.015)	(0.029)	(0.017)
Issuer's rating		–0.838***		–0.787***	0.298***	–0.816***
		(0.021)		(0.023)	(0.039)	(0.034)
Enhancement		–0.093*		–0.087	–0.183*	–0.063
		(0.056)		(0.056)	(0.104)	(0.060)
Sales			–0.221***	–0.057***	–0.021	–0.060***
			(0.008)	(0.010)	(0.018)	(0.010)
Leverage			0.009***	0.005***	0.002	0.005***
			(0.001)	(0.001)	(0.002)	(0.001)
Tangibility			–0.340***	–0.138**	–0.513***	–0.095
			(0.067)	(0.060)	(0.095)	(0.071)
ROA			–0.000	–0.000	0.020***	–0.000
			(0.001)	(0.001)	(0.005)	(0.001)
Growth			–0.006	–0.022	–0.040	–0.019
			(0.022)	(0.019)	(0.035)	(0.020)
Cash equivalent			–0.244***	–0.111***	0.056	–0.117***
			(0.041)	(0.036)	(0.068)	(0.037)
Frequency					0.015***	
					(0.003)	
Constant	2.766***	5.704***	3.286***	5.471***	–1.199***	5.442***
	(0.057)	(0.083)	(0.085)	(0.100)	(0.176)	(0.104)
Hazard						–0.170
						(0.146)
Observations	5065	5065	5061	5061	5061	5061
R-squared (Pseudo R2)	0.144	0.413	0.260	0.421	0.037	
Prob > chi2					0.000	0.000
Industry and year fixed effects	Yes	Yes	Yes	Yes	No	Yes

Appendix 4.6: Bond Issuance Yield and Reputation of Credit Rating Agencies: Propensity Score Matching Sample

This table presents the relationship between the bond issuance yield and reputation of CRAs, using the PSM sample. The sample consists of 11,577 issuance observations from 2006 to the end of 2015. There are 6519 bonds rated by reputable CRAs and 5059 bonds are 1-to-1 matched from the non-reputable group. Columns 1 to 3 present the results for Eq. 4.1 using the PSM sample. The left-hand variable is the treasury spread. All the variables are the same as those in Table 2. The Heckman sample shows results when considering the sample selection bias of choosing reputable CRAs. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels respectively.

	Raw sample			Heckman sample			
				First stage	Second stage		
	(1)	(2)	(3)	Reputation (4)	(5)	(6)	(7)
Reputation	–0.170***	–0.218***	–0.156***		–1.335***	–3.499***	–0.420**
	(0.014)	(0.016)	(0.014)		(0.127)	(0.271)	(0.175)
Maturity	0.069***		0.059***	-0.040***	0.044***		0.055***
	(0.003)		(0.003)	(0.005)	(0.005)		(0.004)
Volume	–0.021**		0.028**	0.061***	0.035**		0.035***
	(0.010)		(0.011)	(0.019)	(0.014)		(0.012)
Issuer's rating	–0.698***		–0.632***	0.100***	–0.608***		–0.621***
	(0.013)		(0.013)	(0.021)	(0.018)		(0.015)
Enhancement	–0.145***		–0.169***	0.023	–0.160***		–0.168***
	(0.026)		(0.026)	(0.045)	(0.033)		(0.027)
Sales		–0.227***	–0.072***	0.055***		–0.044**	–0.063***
		(0.005)	(0.006)	(0.011)		(0.019)	(0.009)
Leverage		0.004***	0.001	0.003***		0.005***	0.001*
		(0.001)	(0.001)	(0.001)		(0.001)	(0.001)
Tangibility		–0.286***	–0.212***	–0.029		–0.172*	–0.207***
		(0.048)	(0.043)	(0.063)		(0.094)	(0.043)
ROA		0.000	–0.000	0.017***		0.003**	0.000
		(0.001)	(0.001)	(0.003)		(0.001)	(0.001)
Growth		0.002	0.001	0.001		0.003	0.001
		(0.001)	(0.001)	(0.002)		(0.002)	(0.001)
Cash equivalent		–0.011***	–0.008*	0.013*		0.005	–0.006
		(0.004)	(0.004)	(0.007)		(0.010)	(0.004)
Frequency				0.015***			
				(0.002)			
Constant	3.848***	2.224***	3.842***	–0.841***	4.122***	3.280***	3.903***
	(0.067)	(0.072)	(0.074)	(0.089)	(0.080)	(0.139)	(0.085)
Hazard					0.729***	2.052***	0.163
					(0.079)	(0.167)	(0.108)
Observations	11,577	11,515	11,514	11,514	11,514	11,514	11,514
R-squared (Pseudo R2)	0.462	0.351	0.470	0.047			
Prob > chi2				0.000	0.000	0.000	0.000
Industry and year fixed effects	Yes	Yes	Yes	No	Yes	Yes	Yes

Appendix 4.7: Variable description

Variable name	Description	Period	Sources
CRAs	21-trading-day CARs (in percentage) for bonds surrounding the rating change announcements of incumbent issuer-pay CRAs	2012-2015	calculation
CCRfirstcover	is a dummy variable equal to one if the event date of rating change is during the post-coverage date, otherwise zero	2012-2015	CCR
CCRcover	a dummy variable that equals one if a firm was rated by CCR at any time, and zero otherwise	2006-2015	CCR
Post	is a dummy variable that equals one if a firm–year–CRA observation is from the period after 2012, and zero otherwise	2006-2015	Wind
Treasury Spread	the difference between the issue's offering yield and the yield on a benchmark treasury security	2006-2015	Wind
Reputable	a dummy variable equals 1 if the bond or firm is rated by joint-venture CRAs, eg., CCXI or Lianhe, zero otherwise	2006-2015	Wind
Maturity	the number of years to maturity of debt	2006-2015	Wind
Volume (log)	the log of the par value of debt initially issued in 100 million of RMB	2006-2015	Wind
Enhancement	a dummy variable indicating the issue has credit enhancements	2006-2015	Wind
Rating	the credit rating assigned to the debt issuer, based on a notch basis as follows: AAA=6, AA+=5, AA=4, AA-=3, A+=2, others=1	2006-2015	Wind
Leverage	the ratio of total liability from the balance sheet to total assets (%)	2005-2014	Wind
Tangibility	the ratio of property, plant and equipment to total assets	2005-2014	Wind
Sales (log)	the log of total sales in 100 Million of RMB	2005-2014	Wind
ROA	the return on assets that represents the profitability (%)	2005-2014	Wind
Growth	the year to year increase of operating income	2005-2014	Wind
Cash equivalent	the ratio of cash, tradable asset and receivable over current asset to represent the liquidity	2005-2014	Wind
Ownership	a dummy variable equals to 1 if the issuer is state-owned company, otherwise zero	2005-2014	Wind
Listed	a dummy variable equals to 1 if the issuer is a public company, otherwise zero	2005-2014	Wind
Frequency	the number of total bond issues conducted by the firm during 2006 to 2015	2006-2015	Wind
IPI	the investor protection index for issuer's registered province	2009	Fan (2011)
MI	the marketization index for issuer's registered province	2009	Fan (2011)
Ind–Mean–Asset	the industry average total asset (measured as the logarithm of total asset) of each firm's industry in the prior year, calculated using only issuer-pay CRA-rated firms not covered by CCR as of 2015	2006-2015	Wind